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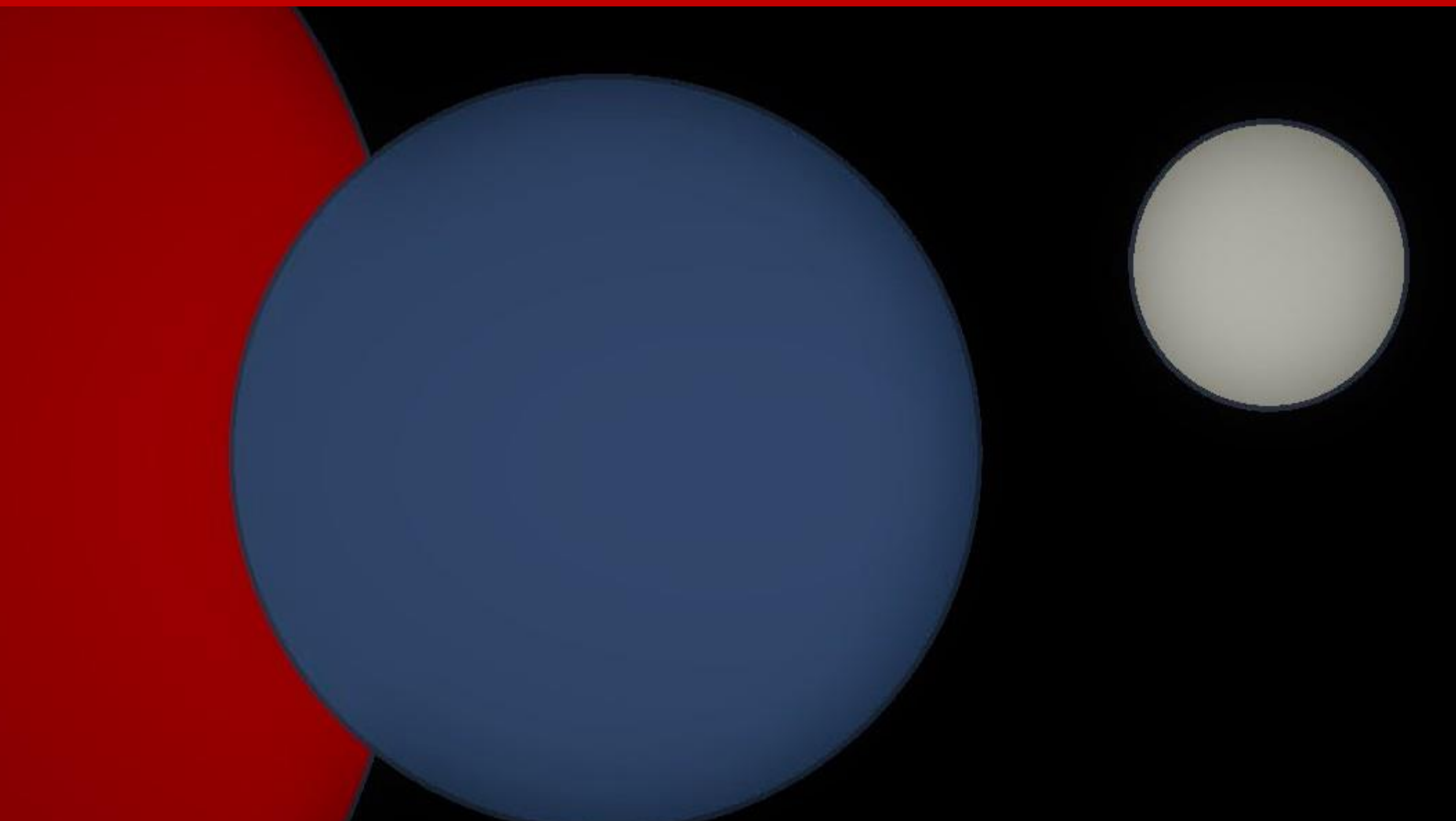

Piercing the "Payoff Function" Veil: Tracing Beliefs and Motives*

Guidon Fenig † Giovanni Gallipoli ‡ Yoram Halevy §

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Abstract

This paper develops an experimental methodology that allows the identification of decision-making processes in interactive settings using tracking of choice-process data. This non-intrusive and indirect approach provides essential information for the characterization of beliefs. The analysis reveals significant heterogeneity, which is reduced to two broad types, differentiated by the importance of pecuniary rewards in agents' payoff function. Most subjects choose actions close to maximizing monetary rewards, by best responding to beliefs. Others are able to identify these actions, but choose to systematically deviate from them – exhibiting either altruistic or competitive motives.

JEL classifications: C9, C92, C72, D9, H41.

Keywords: non-choice data, typology, tracking, response-time, coordination, public goods, complementarity, altruism, joy of giving, competitiveness, joy of winning, complexity, laboratory experiment.

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1 Introduction

There is growing acceptance among researchers that the decision-making processes that agents employ in interactive settings are heterogeneous and often diverge from the principles of standard textbook game theory. Empirical identification of the decision processes adopted by players requires the examination of observed choices in conjunction with richer data that convey information about the way these decisions have been reached.

We develop a simple framework to study, within an experimental setting, the interactions among agents utilizing heterogeneous decision procedures. To identify interactive decision-making processes one needs to posit an environment in which agents' beliefs about other agents' actions affect their pecuniary payoffs. The environment must be such that these beliefs are elicited in a non-intrusive and credible way. The setting must also feature a role for agents to learn about the environment and about the motives and procedures of other agents. An environment with such attributes, and that exhibits multiple equilibria, would be naturally suited to provide new insights into coordination problems. Finally, fine-tuning the pecuniary incentives toward coordination would enable the researcher to assess the intensity of alternative behavioral motives.

This paper proposes an environment that satisfies the key requirements outlined above. We study a joint investment problem in which private investments are made by individual group members, without communication, to generate income that is equally shared. In this problem, an agent's beliefs about the investment of others play a key role in determining her own investment because of the presence of *complementarity* among individual investments. Finding the optimal investment is facilitated by the usage of a calculator whose inputs, which are recorded by the experimenter, provide valuable and reliable information about each subject's thought process and her conjectures regarding other players' investments. We choose not to elicit beliefs explicitly, but we do collect data on the inputs subjects enter in the payoff calculator. These include conjectures about other group members' investments. In Section 5 we describe these data extensively. Collecting process data is easy and common among social scientists in general and experimental economists in particular. However, the type of data we collect, which is the easiest and least intrusive to track, has rarely been analyzed systematically by behavioral economists.[1] Meanwhile, online retailers – like Amazon, advertising platforms – such as Google, or social networks – as Facebook, routinely track both the choices (e.g. purchases, likes, shares) and the process (e.g. search and browsing history) of their users before quoting a price or presenting an advert. A major goal of this study is to demonstrate how systematic analysis of this data may teach us about people's motives, beliefs and reasoning.

Though players in the joint investment problem choose from a continuous strategy space, the game (with selfish players) possesses upmost two equilibria, one at each endpoint of the strategy space. This feature allows us to examine coordination and equilibrium selection. Moreover, manipulating a single parameter within our setting (complementarity) alters the potential gains from coordination, making it possible for the researcher to quantify the monetary cost of pursuing non-pecuniary motives.

For low levels of complementarity, the unique Nash equilibrium (assuming agents are selfish) is a zero-investment equilibrium. When complementarity is sufficiently high, a second full-investment equilibrium emerges, transforming the selection of equilibrium into a coordination problem.

Our experimental design varies the degree of complementarity and includes, as a special case, the well-studied linear public good game. When we introduce complementarity, subjects visibly respond to it. When complementarity is sizable but insufficient to support a second selfish-equilibrium, subjects persistently invest above zero and we observe little or no convergence towards the unique selfish-equilibrium, a behavior consistent with altruistic or "joy of giving" motives. With strong complementarity, subjects are able to move closer to the high-investment Pareto-efficient equilibrium, but fail to reach it – although the monetary incentives and possible altruism motive push in that direction. This suggests another motive - competitiveness or "joy of winning" is at play.

Complementarity between investments is typical of many realistic scenarios of public good provision, especially when individual investments entail costly effort. However, it has

[1] One exception is Cherry, Salant, and Uler (2015) who use a combination of choice and process data to analyze the behavior of participants in an output-sharing game with negative externalities to effort. Their analysis includes the last conjecture subjects enter before submitting a choice and then compares it to actual decisions. Their work is thoroughly discussed in Section 7.

been overlooked to date, as the literature focused on the standard tradeoff between individual (selfish-) rationality and social efficiency. Moreover, complementarity introduces a coordination aspect often required for efficient provision and, through this feature of the environment, we are able to contribute to the study of coordination in games more broadly. We document how individuals form beliefs about other agents' choices, make choices given these beliefs, and how coordination is affected by non-pecuniary motives of some subjects. Section 7 contains further discussion, which also describes the related literature in greater detail.

Combining choice and process data allows us to examine several aspects of the interactive decision-making by subjects. Are conjectures influenced by past experience? Do subjects use the calculator more or less intensively depending on the complexity of the environment? Do subjects adjust their behavior over time and do they use history-dependent best-response strategies? How do they experiment with hypothetical investments and are they able to find the profit-maximizing strategy, given their conjectures? Can we classify subjects according to the processes they adopt to make choices? And how does heterogeneity matter for response times?

To answer these questions, we rely on a wealth of process data, including accurate information about calculations made by each subject before submitting a choice and how long it takes to submit a choice. We document a variety of facts about the way subjects form conjectures about other players' investments, whether subjects are able to identify profit-maximizing responses to their conjectures, and how these calculations relate to their choices.

One objective of our work is to develop a methodological approach to characterize the distributions of choice and process data with minimal restrictions on their joint behavior and on the motives, and calculations, of subjects. By relating the entire distributions of choices and conjectures we show that researchers can draw meaningful inference about the mechanics of decision making.

Our methodological focus on aggregate distributions allows us to distinguish between coherent and incoherent beliefs. This is an essential step prior to drawing conclusions about non-pecuniary motives. To implement this preliminary step, and distinctly from previous work, we also gather data on the distribution of multiple hypothetical investments by subjects; we do so without restricting calculator usage, possible investments and associated payoffs.

This results in an unusually rich set of choice-process records, covering multiple rounds and linking current and past conjectures about other players to each subject's hypothetical and actual choices.

We show that one can break down departures from money-maximizing strategies into two components: deviations due to confusion and non-pecuniary motives. In section 5.4 we illustrate how these elements can be identified from repeated snapshots of the cross-sectional distribution of conjectures, hypothetical and actual choices.

The methodology we develop is flexible insofar deviations are not attributed ex-ante to specific motives. In this respect, not only we can measure the magnitude of non-pecuniary motives, but their scale is elicited from varying the complementarity in the experimental setting without making strong assumptions about agents' preferences.

Analysis of both choice and process data suggests that one can reduce the rich heterogeneity in observed investments to two *modus operandi*, which we associate with two different types of agents: *Homo pecuniarius* and *Homo behavioralis*. *Homo pecuniarius* are able to approximately calculate optimal actions that maximize monetary-profits given their beliefs, which are shaped by recent history. *Homo behavioralis*, on the other hand, are able to identify similar profit-maximizing actions, but choose to systematically deviate from them. We do not find strong evidence of confusion: both types hold coherent beliefs that align with the aggregate distribution of strategies in the population. Moreover, *Homo behavioralis* subjects appear willing to sacrifice some pecuniary rewards to pursue other goals. When complementarity is low, some agents may have altruistic motives and they invest above their monetary best response. When complementarity is high, altruistic behavior is indistinguishable from profit maximization, but a new competitive motive surfaces: by lowering their investment below the pecuniary best response, some subjects are able to obtain relatively higher monetary profits than other participants.[2] This competitive motive was proposed by Fershtman, Gneezy, and List (2012), and the current paper is the first demonstration of how it hinders efficiency even when selfish preferences are aligned with efficiency. Unlike previous field data

[2]In the low-complementarity treatment, competition is indistinguishable from profit-maximizing behavior.

that relied on the ethnic rivalry to explain costly deviation from efficient coordination (Hjort, 2014), our subjects are mostly homogeneous and anonymous. The competitive motive is related to Imas and Madarasz (2020) dominance-seeking, but in our setup a player's utility is increased if she earns more than other group-members, even if she cannot exclude them. Moreover, we quantify the magnitude of these behavioral motives and show that, while relatively modest, they may lead to systematic deviations from the pecuniary best response and to novel aggregate outcomes.

The two types of agents coexist and respond to each other in equilibrium. This is implied by the fact that their beliefs are coherent, in the sense that they are consistent with the empirical distribution of investments. *Homo pecuniarius* pursue approximate monetary best responses based on their coherent beliefs. *Homo behavioralis* can similarly calculate approximate monetary best response to their beliefs, but choose different investment levels that reflect motives other than money. Their dynamic interactions shape aggregate outcomes and provide a way to interpret the choices we observe under alternative degrees of complementarity.

The experimental methodology we propose, together with the exogenous variation in the degree of complementarity, provides a transparent way to study heterogeneity in response times and its relationship to altruism or competitiveness. We show that the time it takes subjects to make a decision depends on the complexity of the environment, on their type (as described above) and on the intensity of complementarity. This implies that analyzing response times while not allowing for sufficient variation in the environment may provide only a partial view on the heterogeneity of the decision-making process.

Although we are primarily interested in the interactive decision making process of (possibly heterogeneous) agents, our work touches on three other areas of research. First, our analysis of rich data describing the agents' decision-making activities is naturally related to a small but fast-growing literature using non-choice data to investigate the way individuals process available information to reach decisions. Furthermore, our experimental setting posits a risky investment problem which includes as a special case the linear voluntary contribution mechanism (LVCM) studied in the extensive literature on public good games. Finally, the presence of multiple equilibria in some of our experimental parameterizations introduces coordination issues that are typically examined in work on equilibrium selection using order-statistic and stag-hunt games. We discuss how our work relates to these important areas of research in Section 7.

The paper is organized as follows. Section 2 presents an overview of the model and selfish-equilibrium predictions. The experimental design and laboratory procedures are described in Section 3. In Section 4 we report results from aggregate data and show how investment behavior varies depending on the degree of complementarity in the environment. Section 5 explores individual-specific behaviors. The combined use of choice and process data is instrumental in explaining deviations from the profit-maximizing strategies and to classify subjects into types. In this section, we also estimate the magnitude of altruistic and competitive motives. In Section 6 we provide an extensive analysis of response times, processing speed and intensity of calculator usage by different subjects. Section 8 summarizes results and concludes.

2 The Joint Investment Problem

Consider a set of n individuals indexed by $i \in \{1, ..., n\}$, each endowed with $\omega > 0$, who must decide whether—and how much—to invest in a joint account that transforms private investments into income that is equally shared among all group members. Let g_i denote individual i's investment. The remainder of the endowment $(\omega - g_i)$ is kept in a private account of player i. Individual investments are aggregated in the joint account through a constant elasticity of substitution production function that exhibits constant returns to scale. Player i's preferences are additively separable between the private and joint accounts:

$$\pi_i = \omega - g_i + \beta \left(\sum_{i=1}^{n} g_i^{\rho} \right)^{1/\rho}, \qquad (2.1)$$

where $\rho \leq 1$ denotes the degree of complementarity and $\beta > 0$ is a constant. This joint investment problem encompasses as a special case (when $\rho = 1$) the standard Linear Voluntary Contribution Mechanism (LVCM). The individual's return from investing depends on the investments of all n players and on the degree of complementarity. The marginal per capita return (MPCR) on investments is $\beta\left(\sum_{i=1}^{n} g_i^{\rho}\right)^{\frac{1-\rho}{\rho}} g_i^{\rho-1}$, and it reduces to the customary β in the linear case.

Equilibrium

The best response (BR) of agent i, denoted as $g_i^*(g_{-i})$ is

$$g_i^*\left(g_{-i}\right) = \begin{cases} kM_{\rho}(g_{-i}) & \text{if } \; kM_{\rho}(g_{-i}) \leq \omega \\ \omega & \text{otherwise.} \end{cases} \tag{2.2}$$

The best response is a linear function of the generalized ρ-mean (M_{ρ}) of their conjecture about the investments of other group members,[3] denoted by the vector $g_{-i} \in \Re_{+}^{n-1}$. Here, $k \equiv \left(\frac{n-1}{\beta^{\frac{\rho}{\rho-1}}-1}\right)^{\frac{1}{\rho}}$ is a constant that depends on the model's parameters. Details on the derivation of the best response can be found in Appendix A. If $k > 0$, the investments are complementary; moreover, as the degree of complementarity diminishes (ρ increases), k decreases as well. In the limit, when ρ approaches 1, k goes to zero and the best-response of player i is to invest zero in the joint account regardless of other players' investments. Because agent i's best-response depends on the generalized mean of g_{-i}, it depends also on the dispersion of other players' investments: for a given arithmetic mean, player i's optimal investment decreases as the dispersion of other players' investments increases. Put simply, there is an additional benefit from coordination. Figure 2.1 summarizes the monetary best-response $g_i^*\left(g_{-i}\right)$ for different values of the complementarity parameter ρ (each used in the experiments that follow).

Imposing the symmetry condition $g_i + \sum_{j \neq i} g_j = ng_i$ in Equation (2.2) and solving for g_i, we characterize the symmetric equilibria:

$$g_i^{eq} = \begin{cases} 0 & \text{if } \; k < 1 \\ \{0, \omega\} & \text{if } \; k > 1. \end{cases} \tag{2.3}$$

[3] The generalized ρ-mean of g_{-i} is $M_{\rho}(g_{-i}) \equiv \left(\frac{\sum_{i=1}^{n-1} g_{-i}^{\rho}}{n-1}\right)^{1/\rho}$. The arithmetic mean is a special case of the generalized mean when $\rho = 1$. The arithmetic and the generalized means are identical when all investments are equal, that is when $g_{-i} = g\mathbf{1}_{n-1}$.

Thus, for given β and n and with sufficiently high complementarity, there exist two equilibria. It is straightforward to verify that only symmetric equilibria in pure strategies exist (see Appendix A.1).[4] It is worth noting that when there are two equilibria, only the full-investment equilibrium is stable.

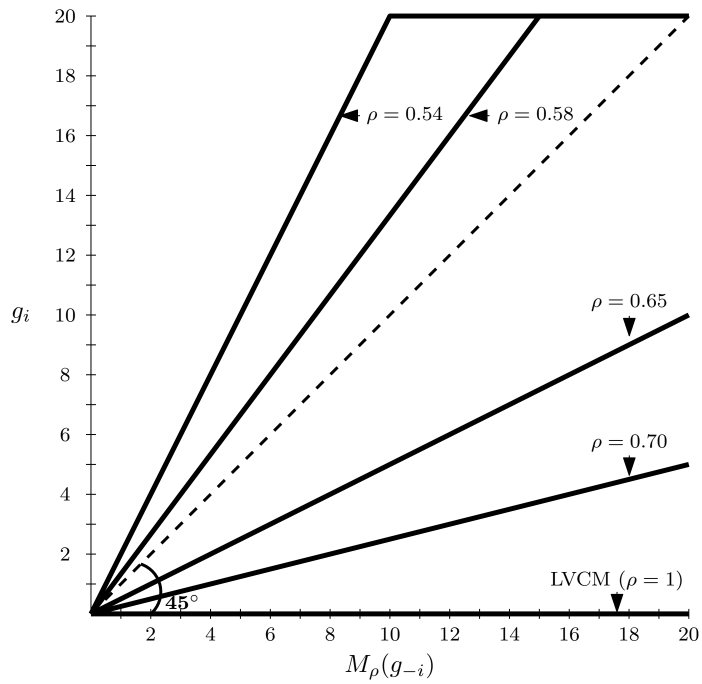


Figure 2.1. Monetary best-response functions. In this figure the x-axis shows the generalized mean of others' investments; the y-axis displays player i's monetary best-response investment. The figure shows the best-response as a function of others' investments, $g_i^*(g_{-i})$. The solid lines represent $g_i^*(g_{-i})$ of player i.

3 Experimental Design

The baseline parameters are chosen so that the linear treatment ($\rho = 1$) is easily comparable to similarly parameterized LVCM experiments (see, among others, Fehr and Gächter, 2000; Kosfeld et al., 2009; and Fischbacher and Gächter, 2010). Specifically, the group size is $n = 4$, initial token endowment of $\omega = 20$ and $\beta = 0.4$. The latter is a commonly assumed value of the MPCR in the linear case. In the nonlinear case, however, the MPCR also depends on the curvature parameter ρ and on investments of other players.

Given the above parameters, the threshold value of ρ that generates an additional full-

[4]Alternatively, $k \gtreqless 1$ if and only if $\rho \lesseqgtr \frac{\ln(n)}{\ln(n/\beta)}$.

investment equilibrium is approximately 0.602. Our treatments consist of variations in the degree of complementarity, ρ. Table 3.1 presents an overview of the experimental design. Treatments are classified as LC (low-complementarity) if ρ is 0.65 or 0.70, which are above the threshold and support a unique equilibrium of 0 investment. If ρ equals 0.54 or 0.58, which are below the threshold and support the additional full-investment equilibrium, the treatments are classified as HC (high-complementarity).

Table 3.1
Experimental Treatments

Treatment Group	ρ	Number of Sessions	Equilibrium Investment
LVCM	1	2	{0}
LC	0.70	2	{0}
	0.65	2	{0}
HC	0.58	2	{0,20}
	0.54	3	{0,20}

3.1 Experimental Procedures

In each experimental session, we recruited 16 subjects with no prior experience in any treatment of our experiment. Subjects were recruited from the broad undergraduate population of the University of British Columbia using the online recruitment system ORSEE (Greiner, 2015). The subject pool includes students with many different majors.

All sessions were computerized using the software z-Tree (Fischbacher, 2007). Upon arriving at the lab, subjects received a set of instructions (see Appendix L). After reading the instructions, subjects were required to answer a set of incentivized control questions.[5] The experiment started after all participants answered all control questions correctly. At the beginning of each round of the experiment, subjects were matched with three other participants. They then played the static game described in Section 2. This process was repeated 20 times. To avoid reputation effects we used a strong version of the stranger

[5]The goal was to facilitate subjects' familiarity with the main features of the framework. Relevant features include (a) decreasing marginal productivity in the group account given a fixed level of others' investments, (b) efficiency gains due to coordination, and (c) absence of a dominant strategy (for treatments in which $\rho < 1$). Subjects were credited \$0.20, \$0.15 or \$0.10 for each question answered correctly in the first, second and third attempt, respectively. There were 19 control questions, which can be found in Appendix K.

matching protocol. Group composition was predetermined and unknown to the participants. We pre-selected the groups so that each pair of subjects interacted only four times, and each time the other two participants were different. This meant that any given grouping of four players never occurred more than once. At the end of the experiment, subjects were paid the payoff they obtained in a single randomly selected round.

The sessions were conducted at the Experimental Lab of the Vancouver School of Economics (ELVSE) at the University of British Columbia, in January 2015 and March 2017. The experiments lasted 90 minutes. Subjects were paid in Canadian dollars (CAD). On average, participants earned \$30.60. This amount includes a \$5 show-up fee and the cash received for the control questions.[6]

3.2 Calculator and Decision Interface

Given the difficulty of computing potential earnings using the nonlinear payoff function, we provided subjects with a calculator interface. Figure 3.1 displays a screenshot of the calculator and decision screen interface. Through this interface subjects were able to enter as many combinations of hypothetical choices and conjectures of other group members' investments as they wished, visualizing the potential payoff associated with each combination. Every time a subject clicked on one of the "OK" buttons the calculator would display her hypothetical payoff (based on her conjectures and hypothetical investment). Subjects were shown their overall income and the breakdown between their private account income and group account income. The subject could easily infer the hypothetical income of other group members (based on the combination she entered), since their group income is identical to hers and any difference is due to difference in investments (20 minus private account income). We then recorded her inputs, potentially many combinations in a single round. In each round, subjects had 95 seconds to submit their chosen investment on the right hand side of their screen.[7] At the end of each round, subjects were informed about their own earnings and the

[6]The exchange rate used in each treatment was adjusted so that expected payoffs in the Pareto efficient allocation were similar across treatments. The exchange rate (dollars per tokens) was set to: 1 for $\rho = 1$; 0.5 for $\rho = 0.65$ and $\rho = 0.70$; 0.4 for $\rho = 0.58$; and 0.33 for $\rho = 0.54$. The profits, and elasticities of the profit function with respect to own and others' investment, are discussed in Appendix B.

[7]For the majority of subjects, this time limit was not binding. To make sure they submitted their decision before time was up, a warning message was displayed 10 seconds before the deadline. During these

investment choices of other group members. Figure J.2 shows the screenshot of the feedback given to subjects at the end of each round.

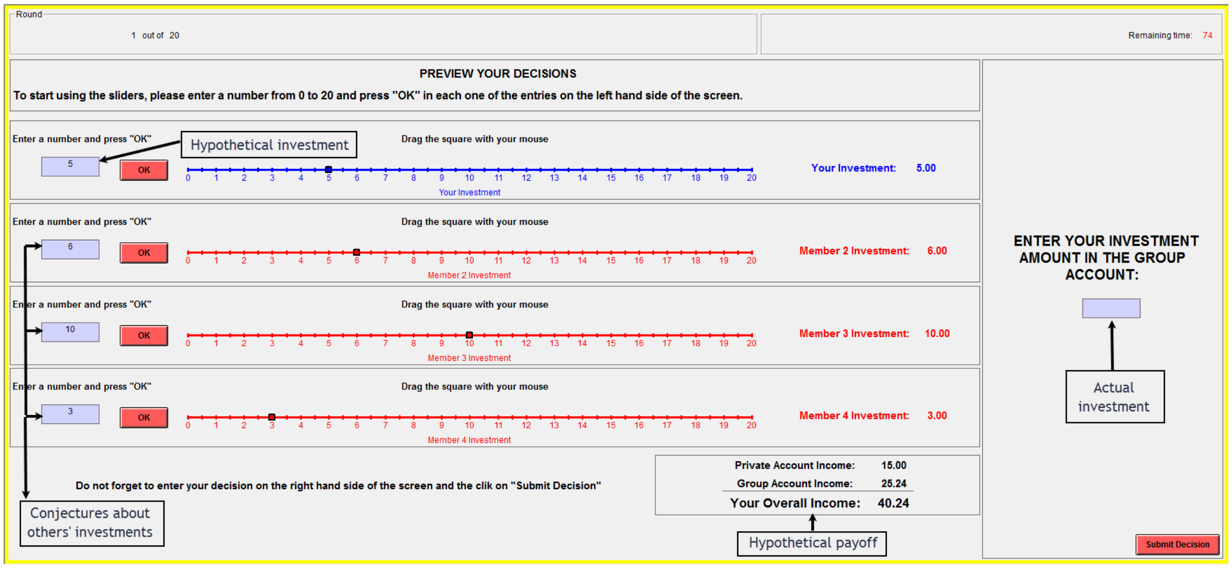


Figure 3.1. Calculator interface: own hypothetical investment is the top ruler; conjectures about others' investments are the bottom three rulers.

4 Average Investment by Treatment

This section examines how changes in the degree of complementarity are reflected in the level and evolution of aggregate investment. Manipulating the degree of complementarity induces stark changes in subjects' behavior.[8]

The five treatments are classified into three groups, as discussed in Table 3.1. In the LVCM (no complementarity), investing 0 is a dominant strategy for any combination of others' investment. In the Low Complementarity (LC) treatments, the unique NE is to invest zero. Still, the best response to any strictly positive combination of others' investments is a strictly positive investment. So the difference between the two levels of complementarity reflects the marginal incentive to lower the investment level in the group account, but not the equilibrium. In the High Complementarity (HC) treatments, there are two Nash equilibria – a full-investment one (with full basin of attraction) and another of zero investment (which is non-stable). Here, too, the difference between the two levels of complementarity is the

last seconds, the payoff calculator was disabled.

[8]We concentrate here on average investment. The dispersion of investments is analyzed in Appendix C.

marginal incentive to increase the investment level in the group account. We, therefore, expect the main differences between ρ levels within a group to affect the rate of convergence to equilibrium, but not the equilibrium qualitatively.

Each solid line in Figure 4.1 represents the evolution of the average investment over the 20 rounds of each specific treatment. The 95% confidence intervals for LVCM, LC, and HC, are shown in the shaded areas. To account for the possibility that individual investments are correlated across rounds, and that investment levels within a session are interdependent, we cluster the error term at the individual and session level so that estimated standard errors are robust. Details are available in Appendix D. Figure 4.1 clearly shows that average investment increases with complementarity. With the exception of the LVCM treatment ($\rho = 1$), in which average investment converges towards the zero-investment selfish-equilibrium, there is no evidence of convergence to selfish-equilibrium for the LC (low complementarity) treatments. Analogously, there is no convergence to the full-investment selfish-equilibrium in the HC (high complementarity) treatments. It is notable that the average investments in the last five rounds of all treatments are quite stable, which facilitates subjects' ability to rationally anticipate the average investment by other participants.

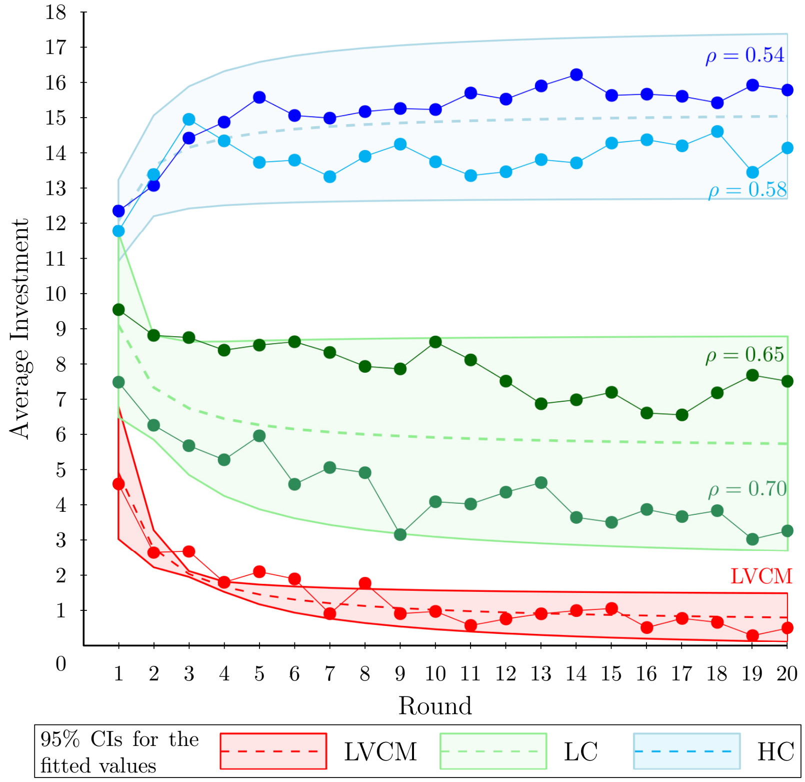


Figure 4.1. Average investment over rounds.

The difference in investments across treatments is substantial, even in the first round when subjects have yet to receive any feedback from other players. Early rounds differences can be partially accounted for by the training subjects received before deciding on investments: their understanding of the rules of the game is reflected in their initial choices.

5 How Do Players Choose Their Investments?

The analysis so far has highlighted that while in the LC or HC treatments there is no visible convergence to selfish-equilibrium, as some subjects persistently deviate from their money-maximizing strategies – over-investing in LC treatments and under-investing in HC treatments – the linear environment exhibits diminishing investments, approaching the unique zero-investment selfish-equilibrium.

In what follows we combine choice and non-choice data to document several important aspects of the choice process. In particular, we examine the scope of history dependence in subjects' decision making and show that investments made by other group members in previous rounds shape each subject's current choices. This history dependence allows us to define a notion of best response to past investments and assess to what extent choices can be rationalized as profit-maximizing behavior.

5.1 The Typology of Subjects

There exist large differences in the behavior of subjects within each treatment. Some invest consistently more than others; many change their choices repeatedly, while others do not. As we document in Section 6 below, and in Appendix E, there is also substantial heterogeneity in the intensity of calculator usage. This suggests that not all agents employ the same decision process when it comes to choosing a particular investment or making choices more generally. To facilitate the analysis, we classify subjects into two broad groups, or types, based on the discrepancy between the payoff associated with the history-dependent best response and the payoff from the actual investment. A larger discrepancy indicates larger foregone earnings. We then examine whether there are differences in the calculator usage of different subject types.

In Appendix F we present evidence of significant history dependence of subjects' beliefs. This is an essential preliminary step and lends empirical support to the ensuing analysis of history-dependent best-responses. To establish the extent of subjects' memory span, we examine the impact of lagged investments by other group members on individual conjectures. We find that conditioning on the previous two rounds accounts for approximately 47% of the variation in conjectures and adding extra lags has no significant effects. To gauge robustness of the empirical analysis, in Appendix F we examine all conjectures from round 2 onwards.[9] We choose to not directly elicit beliefs about others' investments out of concern that this might suggest to subjects that we are deliberately collecting data other than their choices.

[9] About 16% of conjectures coincide exactly with investments by other group members in previous rounds. In 30% of cases, the conjecture matches exactly with one of the 10 possible combinations that can be formed from the group members' investments in the prior round. In 36% of cases, a conjecture matches exactly one of the 56 possible combinations that can be formed from group members' investments in the two previous rounds. These frequencies are extremely high when compared to the three most recurring individual conjectures, namely $(10, 10, 10)$, $(0, 0, 0)$ and $(20, 20, 20)$, which were considered in only 3%, 4%, and 5% of cases, respectively. Agents appear to make conjectures based on recent experiences.

This "observer" effect could influence how they use the calculator, making the experiment more cumbersome and responses less natural.[10]

Pecuniary best responses and the measurement of deviations. How should one use information about investments from previous rounds to define a best-response? Requiring subjects to respond to the triplet of investments observed in any given round seems unreasonably restrictive because subjects are well aware that they will not be matched with the same set of individuals in subsequent rounds. For this reason, we ask if a subject's investment can be rationalized based on a broader notion of recent history and posit that subjects may respond to any possible combination of group members' investments in rounds $t-1$ and $t-2$. For every such combination, and for each subject-round pair, we compute the difference between the profit from the best-response ($\pi_{i,t}^{BR}$) and the profit from the actual choice ($\pi_{i,t}^{ACT}$). Among all the differences computed for a subject-round pair, we keep only the lowest and denote it as $Min\ Loss_{i,t} = \min\left\{\pi_{i,t}^{BR} - \pi_{i,t}^{ACT}\right\}$.[11]

We attempt to rationalize the actual investment as the monetary best-response to a combination of others' investments experienced during the past two rounds. If the investment can be rationalized, then the lowest loss (that is, the $MinLoss$ measure defined above) is zero; if it cannot, the loss provides a monetary metric for the discrepancy relative to optimal pecuniary responses. We can then define the proportional loss as $\frac{Min\ Loss_{i,t}}{\pi_{i,t}^{BR}}$. Given the previous discussion, this is a money-metric index that measures how consistent the actual investments are with the pecuniary-profit-seeking behavior. The final step is to compute the average (over 20 rounds) proportional loss of each subject.

One way to visualize the procedure above is by examining whether the investment chosen by a subject in period t belongs to the convex-hull of the pecuniary best-responses to possible combinations of investments among those observed by the subject in periods $t-1$ and $t-2$. This approach flexibly allows the subject to hold arbitrary beliefs about the likelihood of any such triplet based on recent history.

[10] Since not only the average conjecture is important but also the conjectures' dispersion (and the subject's confidence in her beliefs), an incentivized elicitation would add a layer of unnecessary complexity to the experiment and might confuse subjects more than help the researcher.

[11] We sort the $\pi_{i,t}^{BR}$ values from the highest to the lowest. We then remove the two lowest and highest values. This reduces potential bias due to outlying investments.

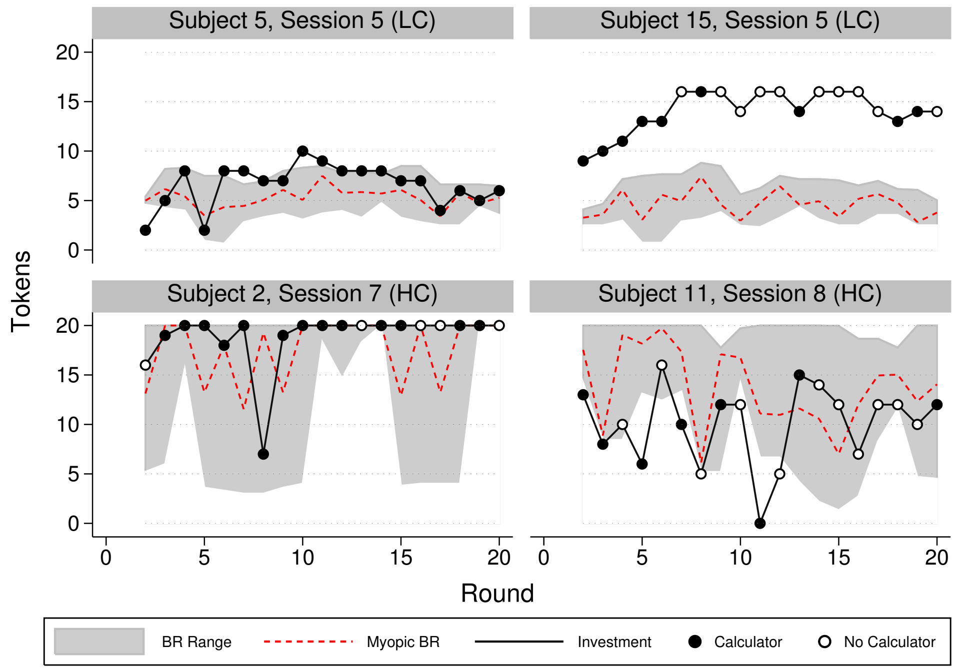


Figure 5.1. BR Range. Investments are juxtaposed to the rationalizable set (gray)—an area consisting of the set of BR. The red dashed line shows the myopic best response. Finally, black (white) dots indicate that subjects activated (did not activate) the calculator.

Figure 5.1 shows investments over time of two subjects in a LC treatment and two subjects in a HC treatment. In Appendix G we present plots of the complete sequence of investments made by every subject. Investments are juxtaposed to the rationalizable set (gray)—an area that approximates the set of best-responses computed using the steps described above. This establishes whether a subject's investment can be rationalized by pecuniary-profit-maximizing motives, and shows how investments drift into and out of the best-response range. In these same figures, we superimpose a dashed red line representing the myopic best-response, to the investments by others in the previous round.

The distribution of types. For each treatment group – LVCM ($\rho = 1$), LC ($\rho \in \{0.65, 0.70\}$), HC ($\rho \in \{0.54, 0.58\}$) – we classify subjects into two subgroups by applying the clustering method developed by Ward (1963).[12] The goal of the method is to minimize the within-cluster variance. Subjects are denoted as Type 1 if they belong to the cluster with

[12] As a robustness exercise, we consider classifications with three types. This results in 11 percent of the subjects classified as Type 3, with no gain in terms of explained variation. For simplicity, we restrict the number of types to two.

lower individual proportional loss, otherwise they are denoted as Type 2. Table 5.1 displays the distribution of types by the intensity of complementarity.[13] It is worth emphasizing again that this grouping criterion requires the joint use of choice and non-choice data.

Table 5.1
Distribution of Types

Type	Treatment Group			Total
	LVCM	LC	HC	
1	17	39	54	114
2	15	25	24	60
Total	32	64	78	174

5.2 Coherence of Conjectures

To assess whether calculator usage by subjects can serve as a reliable tool to measure their beliefs, we inspect if their conjectures are coherent. Beliefs are *coherent* when they coincide with the empirical distribution of investments. In other words, agents hold rational (and, on average, correct) expectations. Holding coherent beliefs is necessary for equilibrium play (Aumann and Brandenburger, 1995), independently of the payoff specification (whether monetary or more general). In our context, it implies that subjects' beliefs about the investments of other participants (whether their own type or the other type) are approximately correct. To examine the hypothesis of coherent beliefs, we compare the aggregate distributions of investments to the distributions of conjectures of Type 1 and Type 2 subjects in each treatment. Conjectures are weighted so every agent who uses the calculator receives an equal weight in the distribution (the weight of every specific conjecture is inversely related to the intensity of calculator usage by the subject). We focus on the distributions of investments and conjectures during the last five rounds (rounds 16-20), since in earlier rounds subjects have been learning the distribution of investments by others. In contrast, subjects experience sampling variation from a known distribution of investments during the later rounds (because they have been matched with some of the same participants in early rounds) rather than from a fully uncertain distribution of aggregate investments. Figure 4.1

[13] In HC treatments we exclude two subjects whose individual proportional loss was significantly higher than the average of subjects classified as Type 2.

lends further support to the assumption of a stationary aggregate distribution of investments during the last five rounds. In Appendix H.1 we report the evolution of average conjectures from practice and early to later rounds. In Appendix H.2 we also document that there is no between-type selection into calculator usage.[14]

Figure 5.2 shows that, for both types and treatments, the cross-sectional distributions of conjectures closely track those of investments. It is important to emphasize that this finding is not mechanical, as there is nothing in the experimental design that might induce investments and conjectures to be distributed so similarly. Sampling from the distributions of investments and conjectures confirms that conjectures of both types are coherent with the aggregate empirical distribution of investments (see Appendix I.3.1). We do not plot the LVCM treatment because this is the only environment in which conjectures are never relevant for the monetary-payoff (it is a dominant strategy to invest 0 in the joint account). Moreover, most Type 1 subjects use the calculator only in the earlier rounds of the LVCM, as they appear to rapidly figure out the monetary-optimal investment level.

5.3 Linking Types to Behavior

Having established that subjects' beliefs are coherent, we turn to investigate what leads Type 2 subjects to deviate from profit-maximizing investments. We consider the hypothesis that over-investment in LC treatments may reflect motives beyond simple profit-seeking. For example, some agents may find joy in the act of investing in the group account, possibly because it increases other subjects' payoff. Such joy of giving would be harder to identify when complementarity is high and profit-seeking behavior dictates high investments.

Similarly, under-investment in HC treatments might reflect a competitive motive, as suggested by Fershtman, Gneezy, and List (2012); a subject who reduces her own investment can guarantee the highest payoff in the group to herself. This motive is indistinguishable from pecuniary profit-maximization when the complementarity is low, since they both lead

[14] Table H.2 shows that, in LC treatments, 64% of subjects activate the calculator during rounds 16-20 whereas, in HC, 36% of subjects activate it during the last 5 rounds. As we show below, HC is an easier strategic environment than LC, so this is not surprising. The absence of systematic selection is substantiated by the observation that calculator usage does not vary with type. In LC, 61% of subjects are of Type 1 and 59% of those who activate the calculator are of Type 1; in HC the unconditional share of Type 1 subjects is 69%, while conditional on activating the calculator their share is 71%.

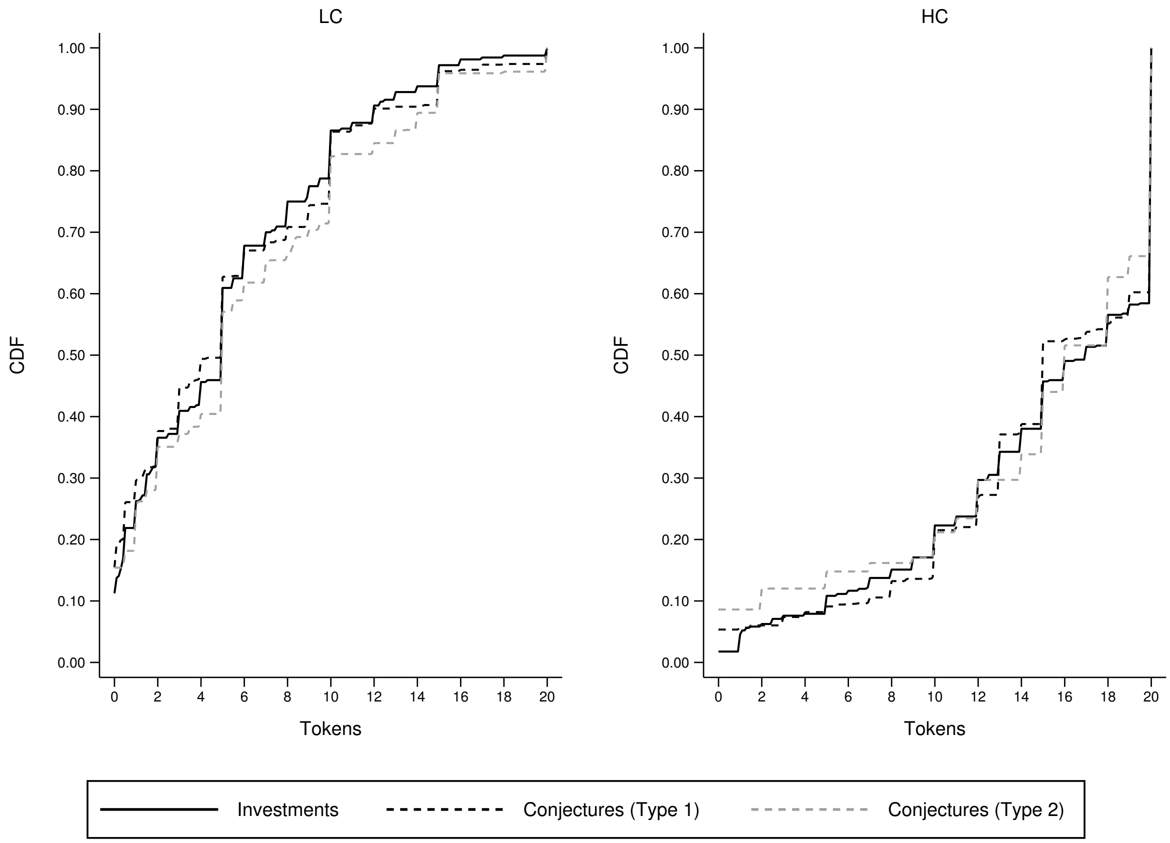


Figure 5.2. CDF of Conjectures and Investments (Rounds 16-20)

to lower investments.

An alternative conceivable hypothesis is that subjects, even those who are profit-seeking, may deviate from profit-maximizing investments because they are confused and do not understand the rules of the game. Given their conjectures, they may simply fail to calculate the profit-maximizing investments.

To discriminate between confusion and behavioral motives, we examine "payoff-relevant" usage of the calculator. We outline simple procedures to identify whether subjects are able to compute the pecuniary best-response to their conjectures using the calculator and if subjects of different types vary in their ability; we then proceed to explore potential differences between types in how their actual investments are related to their calculated hypothetical investments.

5.3.1 *Homo pecuniarius* versus *Homo behavioralis*

For each treatment and subject type, Figure 5.3 displays the cumulative distribution functions of: (i) hypothetical investments, (ii) actual investments, and (iii) best-responses to conjectures. The distributions are based on choices and calculations made by all subjects. Details on the computation of the CDF of hypothetical investments are contained in Appendix I.1.

The CDFs of actual investments of Type 1 and Type 2 subjects are significantly different in all treatments (see tests in Appendix I.3.2). We therefore turn to investigate where does this difference originate from? Sub-section 5.2 documents that the beliefs of both types are coherent, so differences in investments cannot be attributed to differences in beliefs. We are left with two possibilities as to the origin of different choices: differences in the understanding of the environment and in calculating pecuniary best responses, or alternatively – differences in choosing an investment after calculation of hypothetical choices.

In LC, the CDFs of hypothetical investments of Type 1 and Type 2 subjects overlap. In HC, the CDFs are very close (but do not exactly overlap, see Appendix I.3.3).[15] We are therefore led to the conclusion that differences in actual investments reflect how the different types of subjects follow their hypothetical investments. Type 1 subjects (*Homo pecuniarius*) consistently pursue their hypothetical choices, whereas Type 2 individuals (*Homo behavioralis*) opt to frequently deviate from them (see Appendix I.3.4). This is true in all treatments: in LC, Type 2 subjects make altruistic investments (actual investments are much higher than hypothetical investments); in HC environments, Type 2 pursue competitive motives (actual investments are much lower than hypothetical investments).[16]

Calculator utilization varies with the complexity of the treatments. In HC treatments, it is relatively simple to mentally calculate pecuniary best responses. Some subjects who

[15] In LC, hypothetical investments of both types are about 2-3 tokens higher than the pecuniary best-responses to conjectures. In HC, between 60% and 70% of hypothetical investments coincide with the pecuniary best response of full investment. The remaining cases are just 1-2 tokens lower than pecuniary best-responses.

[16] Out of concern for potentially priming investment decisions, we use a between-subject design. For this reason we cannot make claims as to the identity of types across treatments. That is, an agent who over-invests relative to pecuniary best-response in a low complementarity environment might, in principle, under-invest had she participated in the HC treatment. The opposite pattern may emerge as well, but we are unable to establish any such patterns since agents do not participate in different treatments.

do not activate the calculator may form mental representations of similar objects, as it is often straightforward to establish that the pecuniary best-response for many conjectures is full-investment. In LC treatments, it can be challenging to figure out the pecuniary best response without the aid of the calculator.

In Appendix H we present more evidence that using the calculator provides the analyst with an important control to observe subjects' beliefs and verify their understanding of the experimental environment. Figure H.1 depicts the CDF of actual investments and hypothetical investments by treatment and type, for subjects who activated the calculator during the last 5 rounds (left) and those who did not (right). In LC treatments, the hypothetical investments of both types are very close. However, while actual investments of Type 1 approximate their hypothetical investments, the investments of Type 2 are much higher. In HC treatments, among subjects who activate the calculator during the last 5 rounds, the emerging picture is similar: hypothetical investments of both types are very close, but while Type 1's investments are close to their hypothetical choices, Type 2 invest much less. Focusing on subjects in HC who do not activate their calculator, we find that Type 1 subjects make hypothetical and actual investments that are very close to pecuniary best-responses (about 67% of them make full investment). Their investments are even higher than those of Type 1 subjects who use the calculator. This suggests that many subjects can mentally optimize in late rounds (they represent 34 out of 73 subjects who do not use their calculators in rounds 16-20, in both LC and HC treatments). Hypothetical investments of Type 2 subjects in HC who do not activate their calculator in late rounds are lower than pecuniary best-response (only 45% are full investment), and their actual investments are even lower (only 6% are full investment). This suggests that non-pecuniary motives are still important for this sub-group, although some of them (less than 10 subjects) are possibly confused.

As mentioned above, both the variation in the degree of complementarity and the magnitude of optimal investments may affect non-pecuniary motives. When pecuniary best-response investments are low (LC treatments) some agents may enhance their overall payoff through small altruistic over-investments. Such joy of giving could be tainted, or less salient, in an environment where profit maximizing is associated with a high investment. By the same token, when the optimal investment is high, a competitive motive becomes more ap-

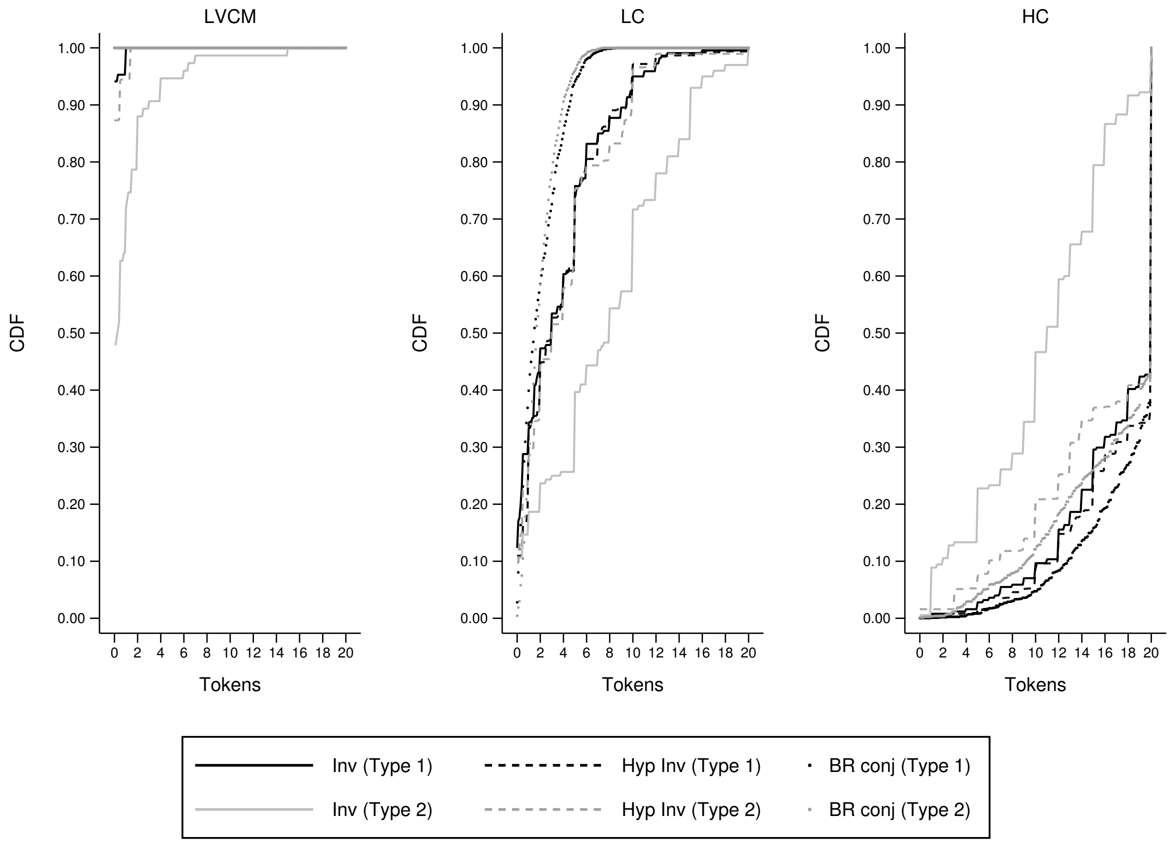


Figure 5.3. CDF of Hypothetical Investments, Actual Investments and Best Response to Conjectures (Rounds 16-20).

pealing as some agents recognize that small reductions in investment are both costly to other players and useful to boost their own relative standing within the group. This competitive motive is indistinguishable from pecuniary-profit-maximizing in LC environments. In fact, behavioral motives may operate side by side with profit-seeking behavior as agents consider all these aspects in their decision making. This observation motivates the following analysis.

5.4 Deviations from Pecuniary Best-Responses: Loss Decomposition

The analysis so far suggests that most deviations from profit-maximizing strategies cannot be accounted for by confusion or miscalculation. Type 2 subjects, in particular, appear to pursue a combination of monetary and non-monetary goals, which results in lower pecuniary payoff. To further quantify the relative importance of confusion and behavioral motives for subjects' decisions, we decompose their monetary consequences (monetary payoff loss) into two distinct components: the first can be interpreted as an upper-bound on the loss that could be attributed to confusion, if present; the second captures any losses above and beyond what can be explained by confusion. As we demonstrate below, the monetary loss of confusion is rather small and the bulk of monetary losses relative to pecuniary-optimal investments are attributable to alternative motives that drive a wedge between investment choices and pecuniary best-responses.

The approach we take in the decomposition is the following: given a triplet of investments by others, there is a total monetary loss incurred by choosing the actual investment rather than the pecuniary-optimal investment. We decompose this loss into a *Hypothetical Loss Index*, which measures what proportion of it is due to not being able to figure out the monetary-optimal *hypothetical* investment (entered into the calculator), and a *Behavioral Loss Index* that measures the proportion of the monetary loss that cannot be attributed to failure to calculate the monetary-optimal investment.

5.4.1 Loss due to Confusion

An upper bound on the loss that is due to confusion can be calculated by measuring the decrease in monetary payoff associated with deviations of hypothetical investments (entered by subjects into the calculators) from monetary best-responses. This calculation is performed by sampling triplets, denoted by g_{-i}, from the empirical distribution of investments made during the last five rounds in each session. For each such triplet, we calculate the monetary best-response, denoted by $g_i^* (g_{-i})$. We independently sample a value $(\hat{g}_i)$ from the empirical distribution of hypothetical investments at the type-session level. We then calculate the difference between the monetary payoff associated with hypothetical investments, denoted by $\pi (\hat{g}_i, g_{-i})$, and the (maximum) pecuniary payoff given g_{-i}, denoted by $\pi (g_i^*, g_{-i})$. Normalizing the difference $\pi (\hat{g}_i, g_{-i}) - \pi (g_i^*, g_{-i})$ by $\pi (g_i^*, g_{-i})$ delivers a loss-function that provides an upper bound on the proportional monetary-loss associated with deviations of hypothetical investments from monetary best-responses, which we call *Hypothetical Loss Index.*

Figure 5.4 plots a histogram of the relative frequencies of the *Hypothetical Loss Index*, showing that most subjects, irrespective of their type and treatment, are able to pinpoint

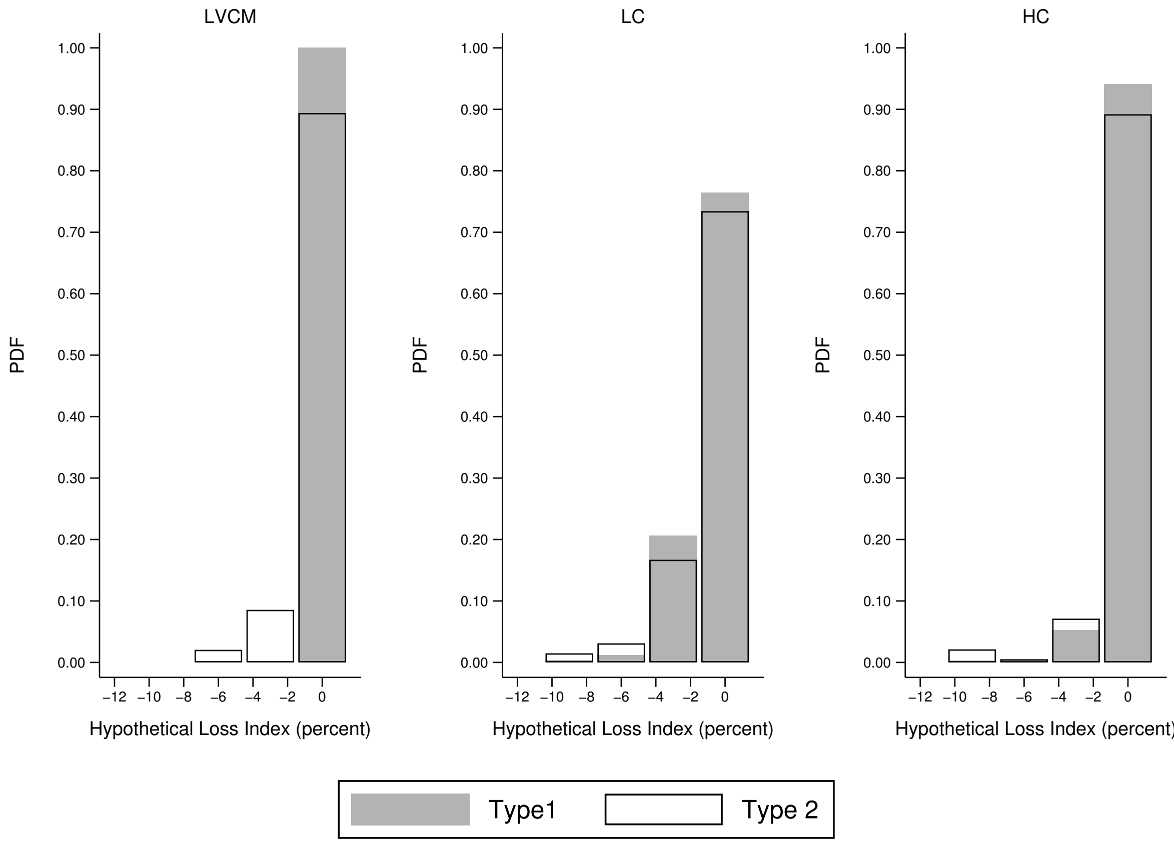


Figure 5.4. Histogram of Hypothetical Loss Index

with remarkable accuracy the monetary best response using the calculator. Table 5.2 presents averages and confidence intervals for *Hypothetical Loss Index* by type and treatment, providing further evidence that most agents have little or no confusion about optimal pecuniary responses. As mentioned before, deviations tend to be marginally larger in the more demanding LC environment. However, even in that setting, most subjects enter hypothetical investments that imply fairly small monetary losses relative to optimal pecuniary investments. Details about how this index is calculated are in Appendix I.2.

Table 5.2
Hypothetical Loss Index

	LVCM		LC		HC	
	Type 1	Type 2	Type 1	Type 2	Type 1	Type 2
Average	0	-0.44	-1.09	-2.12	-0.29	-0.59
95% CI	[0.00, 0.00]	[-1.00, 0.12]	[-2.03, -0.15]	[-3.48, -0.76]	[-0.63, 0.05]	[-2.01, 0.83]

Note: Each cell on the first row reports the average value of the *Hypothetical Loss Index* by treatment and type. The confidence intervals (second row) are obtained by calculating the standard errors of the *Hypothetical Loss Index* at the individual level.

5.4.2 Loss due to Non-Pecuniary Motives

We now turn to construct an index for the willingness to forego monetary returns for behavioral motives. The *Behavioral Loss Index* is the difference between the pecuniary payoff associated with the actual chosen investment and the pecuniary payoff associated with a hypothetical investment (given a triplet g_{-i}, just like the *Hypothetical Loss Index*), defined as: $\pi\left(g_i, g_{-i}\right) - \pi\left(\hat{g}_i, g_{-i}\right)$, and normalized by $\pi\left(g_i^*, g_{-i}\right)$. This difference is defined at the subject-treatment level (details in Appendix I.2).

Figure 5.5 displays histograms of the relative frequency of the *Behavioral Loss Index* for each of the treatments. Unlike the *Hypothetical Loss Index*, there are significant differences between types, which we overview in some detail in Table 5.3. For Type 1 subjects (*Homo pecuniarius*), the *Behavioral Loss Index* is not significantly different from zero on average, suggesting that most subjects generally follow their hypothetical investments. In contrast, Type 2 subjects (*Homo behavioralis*) are willing to forego some monetary rewards; crucially, this occurs even though most of them are able to identify investments that are close to pecuniary best responses, as documented above. One observation in this regard is that Type 2 subjects make choices that are significantly further away from their hypothetical investments (relative to Type 1 subjects) regardless of how close their hypothetical investments are to pecuniary best responses. That lends further support to the hypothesis that alternative behavioral motives, rather than just confusion about the environment, account for their chosen investments.

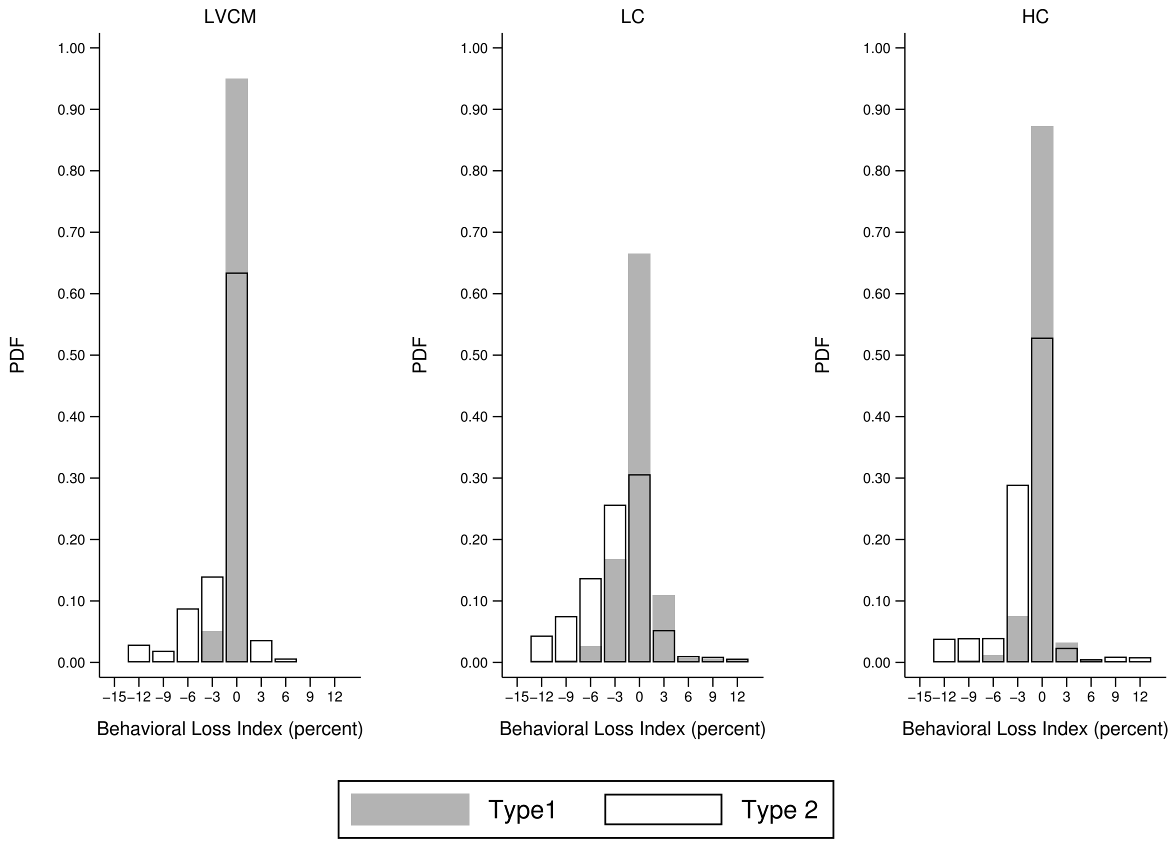


Figure 5.5. Histogram of the Behavioral Loss Index

Table 5.3
Behavioral Loss Index

	LVCM		LC		HC	
	Type 1	Type 2	Type 1	Type 2	Type 1	Type 2
Average	-0.16	-2.56	-0.2	-3.14	-0.23	-1.98
95% CI	[-0.49, 0.17]	[-5.28, 0.36]	[-1.32, 0.92]	[-5.57, -0.71]	[-0.63, 0.17]	[-3.93, -0.03]

Note: Each cell on the first row reports the average value of the *Behavioral Loss Index* by treatment and type. The confidence intervals (second row) are obtained by calculating the standard errors of the *Behavioral Loss Index* at the individual level.

5.4.3 Conditional Cooperation

It is conceivable that some *Homo behavioralis* subjects may try to match other group members' investments, behavior similar to "conditional cooperators" (Fischbacher et al., 2001; Fischbacher and Gächter, 2010). The standard procedure to detect conditional cooperation is to elicit subjects' beliefs about others' investments. Our experimental setting delivers valuable non-choice data – conjectures about others' investments, which we already showed are coherent with chosen investments by others, and can help to identify this behavior. It is important to emphasize that even if all subjects cared only about pecuniary payoff, their best-response function (as shown in Section 2) is an increasing function of their expectations of others' investments, while in the special case of LVCM (which is studied in the literature cited above) investing zero is a dominant strategy for selfish agents.

In Table 5.4 we report results from a regression analysis in which the dependent variable is the investment made by each subject and the right-hand-side variable is the average conjecture about others' investments. For the linear case (LVCM) these results suggest that subjects are willing to match up to 50 percent of what they expect to be the average investment of others. For the case of LC, subjects are willing to invest an amount that is close to what they predict to be the average investment of others.[17] But perhaps the most interesting findings are those in the case of HC, in which a subject who is motivated by pecuniary motives alone should contribute more than the average investment she expects others to make. In other words, in these treatments the conditional-cooperation motives should reinforce the monetary payoff subjects obtain when they coordinate on high investments. In these settings, while we find a positive association between investments and conjectures, investments match only about 60% of the average conjecture. It is apparent that conditional cooperation cannot account for the choices made by *Homo behavioralis* subjects in HC settings, lending further support to the hypothesis that these individuals respond to other non-pecuniary motives, such as competitiveness.

[17] We cannot reject the hypothesis that, in LC treatments, Type 2 subjects make investments that match exactly their average conjecture (we test the null hypothesis $H_0: \hat{\beta} + \hat{\delta}^{\beta}_{LC} = 1$, which results in F=0.14 and $p > F = 0.709$).

Table 5.4

Response of Subjects' Investments to Conjectures about Others' Investments

Variable	Coefficient	Number of observations
$\hat{g}_{-i}$	0.566 (0.087)	94
$D_{LC} \times \hat{g}_{-i}$	0.462 (0.115)	232
$D_{HC} \times \hat{g}_{-i}$	0.056 (0.151)	155

Hypothesis	F	$p > F$
$H_0: \ \hat{\delta}_{LC} = 0$	16.24	0.0001
$H_0: \ \hat{\delta}_{HC} = 0$	0.14	0.7117
$H_0: \ \hat{\delta}_{HC} = \hat{\delta}_{LC}$	7.88	0.0068

Note: Results for the regression: $g_{i,t} = \beta \hat{g}_{-i,t} + \sum \delta_k \left(D_k \times \hat{g}_{-i,t}\right)$, where $g_{i,t}$ is the investment of a Type 2 subject i in round t, $\hat{g}_{-i,t}$ the arithmetic mean of conjectures of Type 2 subject i in round t, D_k is a dummy variable for each complementarity degree ($k \in \{LC, HC\}$), when the baseline is the LVCM treatment. This means that the total effect on LC is 1.028 and the total effect on HC is 0.622. The standard errors (reported in parentheses) are clustered at the individual level. At the bottom part of the table we test for equality of the coefficients.

6 Evidence from Response Times

Using non-choice data we obtain precise measures of subjects' response times and intensity of calculator usage. This information is a valuable way to peek at the mechanics of individual decision making. Analyzing decision times in public good games has become increasingly popular since Rand et al. (2012) reported that shorter response times are positively correlated with higher investments in a one-shot LVCM experiment. This finding was interpreted as evidence that humans are instinctively generous. However, this interpretation has been challenged by, among others, Recalde et al. (2018), who point out that in the LVCM the only possible deviation is to over-invest, making it hard to distinguish between subjects who instinctively over-contribute and those who rush and make genuine mistakes.[18]

[18] Recalde et al. (2018) design a voluntary investment experiment in which the dominant strategy is in the interior of the strategy space, and replicate the finding of Rand et al. (2012) when the equilibrium investment is below the midpoint of the choice space. However, when the equilibrium is located above the midpoint, they find a negative correlation between response times and investments.

6.1 Response Times in the First Round

First, we replicate the analysis of Rand et al. (2012). For comparability, we consider only the first-round investments in the LVCM treatment. The results confirm the findings of Rand et al. (2012): subjects who invest zero wait 34 seconds on average before logging their choice, while for those who make positive investments it takes 25 seconds on average.

Our experimental design allows us to go far beyond the one-shot game and the case of no complementarity. The analysis of later rounds makes it possible to assess how response times are associated with both the size and the direction of deviations of investments from pecuniary best responses. We combine non-choice data and response-time information to illustrate how some of the conclusions about instinctive generosity drawn by Rand et al. (2012) are inconsistent with our findings. More generally, we argue that valuable information can be elicited from variation in the length of time it takes subjects to choose their investments and the intensity of calculator usage over that interval.

6.2 Differences across Treatments and Types

By analyzing the patterns of response times over several periods it is clear that subjects tend to respond faster in later rounds than in earlier rounds (Figure 6.1). This is not surprising given that participants become more familiar with the game at later rounds.

The increase in speed is closely related to calculator usage, which declines as rounds progress. This can be seen in the left panel of Figure 6.2; for this reason, at the end of the section we combine these two measures to compute the average processing speed for each treatment. The right panel of Figure 6.2 shows the five-round moving average of the number of new conjectures as a share of the overall number of conjectures considered in all previous rounds. A steep drop in the percentage of new conjectures is visible after the first few rounds: this is consistent with the hypothesis that most subjects try out conjectures early in the experiment and, as they gain more experience and learn the aggregate distribution of investments, the innovation rate of conjectures declines.

As shown in Figure 6.3 and Table 6.1, we observe considerable differences in the average response time across treatments. Subjects in LVCM treatments take significantly less time

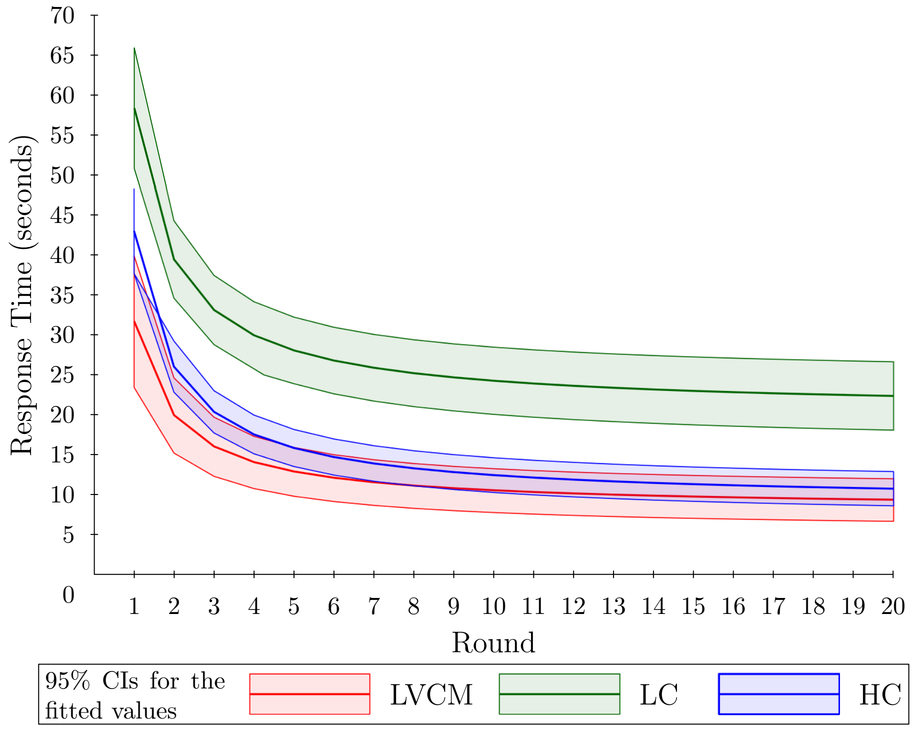
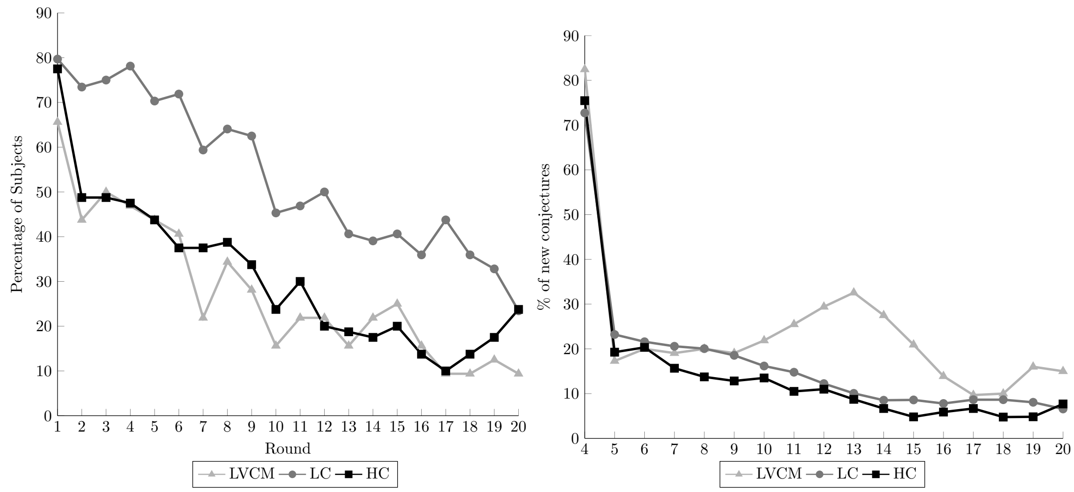


Figure 6.1. Average response time across rounds. This figure shows the evolution of the average response in each treatment. Standard errors (for the confidence intervals) are clustered at the individual level.

than in the LC treatments, suggesting that more complex environments, like LC, elicit more pondering of potential choices. The HC response times lie between those of the two other treatments, suggesting that high complementarity settings are less challenging than low complementarity ones.

We also examine our non-choice data through the lens of the typology described in Section 5.1. This reveals interesting discrepancies between types in both the quantity and quality of time usage. In the LVCM and HC treatments, *Homo pecuniarius* (Type 1) subjects seem to respond faster than *Homo behavioralis* (Type 2). Differences are not significant and we take them with some caution. Nonetheless, the disparity in estimated time use clearly indicates that in one set of treatments (LVCM) the marginally faster subjects are those who invest little or nothing, while in another set (HC) the quicker subjects are those who get closer to full-investment. Hence, both response time and the direction of deviations from pecuniary best responses seem to depend on the specific environment. More importantly, we find little or no evidence that speedy choices systematically and significantly imply over-investment.



(a) Use of the calculator

(b) New conjectures

Figure 6.2. Use of the calculator over rounds. The left panel reports the proportion of subjects who activated the calculator by treatment. The right panel displays the five-round moving average of new conjectures as a percentage of overall conjectures. For period 4 we include data from the practice round, for which the percentage of new conjectures is 100%.

In contrast, in LC treatments, *Homo pecuniarius* subjects take longer to submit their choices than *Homo behavioralis*, possibly because calculating the optimal level of pecuniary investment with precision is harder when complementarity is low. Rubinstein (2007) obtains similar results, finding that it takes more time to make decisions that require cognitive reasoning than to make instinctive choices. Since differences in raw time usage across types in the LC case are poorly identified, we resort to additional measurements to examine the hypothesis that Type 1 agents may try harder to figure out pecuniary best responses; as we show below, agents who play close to pecuniary best response in the LC treatments not only require more time in order to make a choice but also use the calculator more intensively and consider a higher number of potential combinations.[19]

6.3 Processing Speed

Given the evidence presented so far on raw time use data, it is crucial to distinguish between subjects who spend much of their time idly staring at the screen and those who utilize the calculator. To identify this difference we compute the average amount of time subjects

[19] Response times of Type 1 and Type 2 subjects in LC treatments are consistent with the typology described in Rubinstein (2016). He divides subjects into two types according to their response time, arguing that subjects who make quick decisions are more instinctive while those who are slower often make strategic considerations.

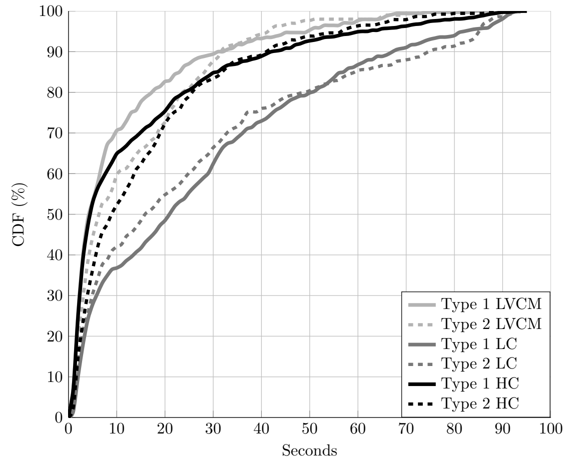


Figure 6.3. Response-time frequencies. Each solid (dashed) line represents the cumulative distribution function for Type 1 (Type 2) subjects for each of the treatments.

spend entering any given combination in the calculator. This is done by dividing the total time spent on the calculator by the number of combinations that are considered during that time interval. The resulting statistic, which can only be computed for those who use the calculator, is a proxy for the speed at which information is processed. The bottom panel of Table 6.1 shows that, across all treatments, *Homo pecuniarius* subjects process more combinations per unit of time than *Homo behavioralis* subjects (the difference is significant in HC treatments).

Moreover, regardless of their type, all subjects process combinations significantly faster in the LC treatments. This provides further evidence in support of the hypothesis that in more complex environments, like the LC, subjects tend to exert more effort when choosing an investment.

7 Discussion of Related Literature

It is often challenging to interpret decision-making through the examination of choice data alone. For this reason, several studies have started collecting non-choice data to shed light on the decision process of players. Throughout each session, we give participants access to a payoff calculator. By using the calculator subjects can see the monetary payoff associated with as many hypothetical investments as they wish, including different hypothetical values

Table 6.1

Response Times and Processing Speed, by Type and Treatment

Response Times, by Type and Treatment

	Type 1		Type 2		Overall	
	Fitted Seconds (SE)	95% CI	Fitted Seconds (SE)	95% CI	Fitted Seconds (SE)	95% CI
LVCM	11.44 (2.36)	[6.82,16.07]	13.62 (1.79)	[10.11, 17.12]	12.46 (1.52)	[9.49, 15.43]
LC	27.76 (2.86)	[22.15, 33.37]	26.57 (3.16)	[20.37,32.77]	27.29 (2.13)	[23.12, 31.47]
HC	14.68 (1.59)	[11.56,17.79]	16.25 (2.02)	[12.30,20.21]	15.19 (1.26)	[12.73,17.65]

Processing Speed, by Type and Treatment
(Response Time Divided by Number of Combinations Entered in the Calculator)

	Type 1		Type 2		Overall	
	Fitted Seconds (SE)	95% CI	Fitted Seconds (SE)	95% CI	Fitted Seconds (SE)	95% CI
LVCM	17.97 (4.30)	[9.52, 26.41]	18.80 (2.53)	[13.83,23.76]	18.43 (2.38)	[13.77,23.09]
LC	14.32 (1.27)	[11.83,16.80]	17.27 (1.88)	[13.58,20.96]	15.41 (1.07)	[13.32,17.51]
HC	15.26 (1.20)	[12.91, 17.60]	21.95 (1.73)	[18.54,25.36]	17.54 (1.06)	[15.47,19.62]

Note: The standard errors are clustered at the individual level.

of their own choice. We record every trial that subjects enter in the calculator during both the practice period and the experiment. These non-choice data are different from information collected using "mouse lab" (see, among others, Camerer et al., 1993; Costa-Gomes et al., 2001; Johnson et al., 2002; Costa-Gomes and Crawford, 2006; and Brocas et al., 2014), "eyetracking" (see, among others, Knoepfle et al., 2009; Wang et al., 2010; Reutskaja et al., 2011; and Arieli et al., 2011), analysis of response times (see Spiliopoulos and Ortmann, 2018 for a literature review), rational inattention analysis (see, among others, Caplin and Dean, 2015; and Dean and Neligh, 2017), choice process (Caplin et al., 2011; Agranov et al., 2015; Kessler et al., 2017), or fMRI techniques (see Bhatt and Camerer, 2005; Smith et al., 2014). When employing these techniques, participants are usually (except for response time) aware that experimenters are gathering data, and this may influence their choices. For example, in experiments employing choice process data, instantaneous decisions are incentivized, making explorations costly. Similarly, although experiments using mouse lab are certainly less intrusive than eye-tracking, they require the subject to interact with the interface in a particular, and at times unnatural, way (usually sequentially revealing payoff-relevant information). Finding the optimal strategy in our investment problem makes the use of the calculator often necessary, as payoff functions are nonlinear, and individual gains are affected by the dispersion of players' investments. For these reasons, subjects depend on the calculator to evaluate alternative strategies and to make informed choices. The input they enter into the calculator delivers a valuable description of their beliefs about the investments of other agents. In this sense, our method provides a non-intrusive way to collect high-quality non-choice data. A further advantage of this approach is that data collection is simple and requires no special technology or equipment; thus, it can be applied easily to the analysis of most individual or group decision problems either in an experimental setting, and even in survey analysis.

Collecting non-choice data is common among social scientists. However, methodologies that rigorously analyze this type of data systematically are rare. One exception is Cherry, Salant, and Uler (2015) who study an output-sharing game with negative externalities, in which subjects' payoffs depend on their own investment choices and the aggregate investment of the other group members. They use a combination of choice and non-choice data to analyze the behavior of participants - own investments and conjectures about the aggregate investment of others. Like us, they extract the conjectures from a payoff calculator, which they call Situation Analyzer (though they retain only the last conjecture subjects enter before submitting a choice). However, our methodology to analyze departures from payoff-maximizing strategies is more comprehensive and flexible for at least three reasons. First, Cherry, Salant, and Uler (2015) approach does not distinguish between correct and incorrect beliefs. We consider this a crucial step that is essential for drawing any conclusions about non-pecuniary motives; otherwise, when observing deviations from the monetary-optimal strategies, it is impossible to disentangle whether deviations are due to incoherent beliefs or behavioral motives. Second, Cherry, Salant, and Uler (2015) do not collect data on hypothetical investments. They ask subjects to enter a conjecture about the aggregate investment of others. Then they display the potential earning given the conjecture. This design feature makes it impossible to identify confusion, as even subjects who barely understand the instructions may select the investment associated with the highest potential payoff displayed on the screen. Thus, the implicit assumption is that subjects do not exhibit confusion, and when deviations from the model predictions are observed, they can be entirely attributed to behavioral motives. In contrast, our methodology allows us to break down departures from the money-maximizing strategy into two main components: deviations due to confusion and due to non-pecuniary motives (as described extensively in section 5.4). Third, Cherry, Salant, and Uler (2015) propose three different competing theories that may account for deviations from the pecuniary best response given subjects' conjectures - altruism, conformity, and extremeness aversion. Then using their choice and non-choice data, they quantify the explanatory power of each of the theories and conclude that subjects exhibit altruism and conformity. In comparison, our approach is more flexible as we do not attribute deviations to a parametric model of preferences. Moreover, unlike Cherry, Salant, and Uler (2015), we are able to measure the magnitude of the non-pecuniary motives.

We design the calculator in a way that allows agents to change one or more conjectures about other agents' investments and/or adjust their own hypothetical investment in whichever order, by any amount and as many times as they want. In this sense subjects are let free to explore the payoff space in countless ways. Our experimental design allows agents to exactly reproduce and modify investments observed in previous rounds, or to consider significantly different scenarios since they face no constraint in the number and type of combinations they are allowed to evaluate. This results in rich distributions of non-choice data that vary over the continuous set of potential investments and can be studied in conjuction with the distributions of hypothetical and actual choices.

It is worth emphasizing that, since our analysis concentrates on the joint investment problem of agents facing non-linear returns, we model these returns as the product of complementary investments and consider treatments with different levels of gains from cooperation. A constrained version of our problem corresponds to the LVCM. This game emphasizes the tension between private incentives and social efficiency, examining how individual choices shape group outcomes. The LVCM assumes a production technology of the public good that is linear and additively separable in agents' investments. Under this assumption (and if the marginal per capita return is lower than one) the dominant strategy for agents with self-regarding preferences is to invest nothing at all (i.e., free ride) rather than make a positive investment that results in a private cost and a social benefit. Hence, this linear specification focuses on the choice problem of an agent whose profit-maximizing choice is independent of other agents' choices.[20] Yet, complementarity is key in many environments in which individual investments entail costly effort. For example, a household may be viewed as a group in which individual efforts are strong complements in generating positive group outcomes. Similarly, modern charities often rely on matching efforts by different stakeholders to raise funds and reach a socially valuable objective. Crucially, in several joint endeavors such as school funding activities, neighborhood improvement initiatives and even scientific research projects, the return on a participant's effort depends on the level of effort that all other participants choose to exert, and too much heterogeneity in individual investments may be detrimental. Identifying how subjects coordinate in such joint investment environments is essential to make sense of empirical observations.[21] In practice, a provision technology featuring complementarity in individual investments captures two essential features of joint investment problems. First, an increase in one's investment raises the marginal return on others' investments and, second, the provision is more efficient when agents' investments are relatively homogeneous.

Lastly, our work is related to the experimental literature that studies coordination failures in games with strategic complementarities in players' decisions. The classic example is the two-by-two stag hunt game in which there are two Nash equilibria in pure strategies, one payoff dominant and the other risk dominant (see Cooper et al., 1992). In this type

[20]The experimental literature is much too vast and thoughtful to be covered fairly here. An interested reader is referred to Ledyard (1995) for an older but helpful survey and a more recent survey by Vesterlund (2016). The robust experimental finding is that contributions are significantly higher than zero in early rounds but diminish over time. Positive contributions have been interpreted, among other explanations, as reflecting confusion, altruism, or willingness to cooperate if others do.

[21]Andreoni (1993) considers complementarity between the private and public good; Keser (1996) studies utility that is non-linear in the private good; Harrison and Hirshleifer (1989); Croson et al. (2005) study public good experiments based on the weakest-link mechanism of Hirshleifer (1983). Steiger and Zultan (2014) compare the linear case and a case in which the marginal return from the public good increases as the number of contributors increases (through increasing returns to scale).

of coordination game, the Pareto superior (payoff-dominant) outcome is not always chosen; the equilibrium selection depends on the basin of attraction and the optimization premium (see Battalio et al., 2001; Van Huyck, 2008). The current study introduces coordination considerations in a public good game. Our experimental result of no convergence to the unique Nash equilibrium in the case of weak complementarity is in sharp contrast to experimental results in binary-action games and suggests that a richer strategy space may induce interesting behavioral dynamics.

When the degree of complementarity supports two equilibria, our game superficially resembles order-statistic games (see Devetag and Ortmann (2007) for a survey of experimental results). The players in these games select an integer number between 1 and k, and their payoff is decreasing in the distance between their chosen number and some order statistic. Order statistic games have multiple Pareto-ranked equilibria and have been studied experimentally in the context of coordination. For example, in the extreme weakest-link game the agent's payoff depends on the minimum of all the chosen numbers. Van Huyck et al. (1990) show that subjects fail to coordinate on the efficient outcome when groups are large. There are, however, important differences between order-statistic games and our joint investment framework. First, order-statistic games do not enable free-riding. Second, in our framework, the earnings from the joint account depend on the investments and on the investments' dispersion, whereas order-statistics games do not account for heterogeneity in players' choices. Finally, in terms of equilibrium selection: coordination in order-statistic games is challenging because there exist $k - 1$ equilibria that are relatively fragile, whereas in our environment only the Pareto-efficient equilibrium is stable.

8 Conclusion

In this paper we examine and compare the dynamic decision processes of individuals who participate in a joint investment problem. We carry out the analysis in an environment featuring complementarity between private investments into a common account. The environment can exhibit multiple equilibria.

Our experimental setting is such that agents' beliefs about other agents' actions affect their pecuniary payoffs. The setting allows us to gather rich information on the way agents learn about the environment and about the motives and procedures of other agents. We do not elicit beliefs explicitly but, rather, collect data on the inputs subjects enter in the payoff calculator. These include conjectures about other group members' investments.

Consistent with theoretical predictions we find a positive relationship between aggregate investments and the degree of complementarity. In HC environments subjects learn to coordinate, moving towards the socially preferable equilibrium, but do not reach the Pareto efficient outcome. Similarly, when complementarity is very low, investments decrease but do not reach the unique zero-investment equilibrium. Subjects also seem to respond to complementarity when its intensity is sizable but not sufficiently high to introduce a second full-investment equilibrium; in this case, they persistently over-invest and show little or no tendency towards the unique zero investment.

The use of detailed choice-process data, together with the manipulation of the intensity of complementarity, allows us to identify the empirical relevance of non-pecuniary motives in the decision-making process. We find that deviations from the profit-maximizing strategy cannot be attributed to confusion and that different types of non-pecuniary motives emerge when we change the intensity of complementarity among individual investments.

Crucially, not all subjects are equally sensitive to non-pecuniary motives. We find evidence that while some individuals (*Homo Pecuniarius*) can be clearly described as profit seekers who are willing to make cognitive efforts to find pecuniary best response strategies, others (*Homo Behavioralis*) are able to calculate the money-maximizing strategy but deliberately deviate from it towards altruistic or competitive actions. The interaction of different types of participants is key to understanding how groups behave and why we observe different aggregate patterns under different levels of complementarity. The fact that *Homo Behavioralis* subjects are willing to sacrifice some monetary rewards to deviate from pecuniary best-response strategies may lead to imperfect convergence to selfish equilibrium, not only as a result of their strategic decisions but also because *Homo Pecuniarius* are aware of their choices and best-respond to them. The presence of *Homo Behavioralis* increases social welfare when complementarity is low, as it restrains group investments from collapsing to zero, but it reduces welfare when complementarity is high and full investments would be optimal.

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A Pecuniary Best-Response Function and Symmetric Equilibrium

Player i's payoff is

$$\pi_i = \omega - g_i + \beta \left(\sum_{i=1}^{n} g_i^\rho \right)^{1/\rho},$$

where $\rho \leq 1$ denotes the degree of complementarity, g_i denotes individual i's investment in the group account, ω is the endowment, and β is a constant. The best response of player i is a unique solution, $g_i^*(g_{-i})$, to the first order condition

$$\begin{aligned}
0 = \frac{\partial \pi_i}{\partial g_i} &= \beta \left(g_i^\rho + \sum g_{-i}^\rho \right)^{\frac{1-\rho}{\rho}} \left(g_i^{\rho-1} \right) - 1 \\
\beta \left(g_i^\rho + \sum g_{-i}^\rho \right)^{\frac{1-\rho}{\rho}} &= g_i^{1-\rho} \\
g_i^\rho + \sum g_{-i}^\rho &= g_i^\rho \beta^{\frac{\rho}{\rho-1}} \\
g_i^\rho \left(\beta^{\frac{\rho}{\rho-1}} - 1 \right) &= (n-1) \frac{\sum g_{-i}^\rho}{n-1}.
\end{aligned}$$

In the last line we multiply and divide the right hand side by $(n-1)$ so the best response of player i is defined as a function of $M_\rho = \left(\frac{\sum g_{-i}^\rho}{n-1}. \right)^{1/\rho}$. Finally, defining $k \equiv \left(\frac{n-1}{\beta^{\frac{\rho}{\rho-1}} - 1} \right)^{\frac{1}{\rho}}$ yields:

$$g_i^*\left(g_{-i}\right) = k \left(\frac{\sum g_{-i}^\rho}{n-1} \right)^{1/\rho}.$$

The second order condition

$$\begin{aligned}\frac{\partial^2 \pi_i}{\partial g_i^2} &= (1-\rho)\beta\left(g_i^\rho + \sum g_{-i}^\rho\right)^{\frac{1-\rho}{\rho}-1} g_i^{2(\rho-1)} + (\rho-1)\beta\left(g_i^\rho + \sum g_{-i}^\rho\right)^{\frac{1-\rho}{\rho}} g_i^{\rho-2} \\ &= (\rho-1)\beta\left(g_i^\rho + \sum g_{-i}^\rho\right)^{\frac{1-\rho}{\rho}} g_i^{\rho-2}\left(1 - \frac{g_i^\rho}{g_i^\rho + \sum g_{-i}^\rho}\right) < 0,\end{aligned}$$

which implies concavity of π_i.

A.1 Pure strategy equilibria are symmetric

Suppose that there exists a non-symmetric equilibrium g^* and denote by $g^*_{min} = min\{g^*\} < max\{g^*\} = g^*_{max}$. For the case of $k \leq 1$, let $(n) = \{i : g_i > g_j \forall j \in N\}$, then if $g^*_{-(n)}$ denotes the vector of investment values different from $g^*_{(n)}$, it follows that $kM_\rho\left(g^*_{-(n)}\right) < g^*_{max}$, which is a contradiction. Similarly, if $k \geq 1$, and $(m) = \{i : g_i < g_j \forall j \in N\}$ it follows that $kM_\rho\left(g^*_{-(m)}\right) > g^*_{min}$, which is a contradiction. Finally, when $k = 1$, any symmetric strategy profile is a Nash equilibrium.

A.2 Absence of symmetric Nash equilibrium in mixed strategies

A symmetric NE in mixed strategies is a joint distribution μ^{n-1} over g_{-i} such that i is indifferent between all $g_i \in supp(\mu)$. In other words, for any two strategies, g_i' and g_i'', in the support of μ, it must be that:

$$\omega - g_i^{'} + \beta \int_{supp(\mu^{n-1})} \left(g_i^{'\rho} + \sum g_{-i}^\rho\right)^{1/\rho} d\mu^{n-1}(g_{-i}) = \omega - g_i^{''} + \beta \int_{supp(\mu^{n-1})} \left(g_i^{''\rho} + \sum g_{-i}^\rho\right)^{1/\rho} d\mu^{n-1}(g_{-i})$$

We will show that g_i^* - the BR of player i to μ^{n-1} is a singleton, and therefore there is no symmetric NE in mixed strategies. The first order condition is:

$$\frac{\partial \pi_i\left(g_i, \mu^{n-1}(g_{-i})\right)}{\partial g_i} = -1 + \beta \int_{supp(\mu^{n-1})} g_i'' \left(g_i^\rho + \sum g_{-i}^\rho\right)^{\frac{1-\rho}{\rho}} g_i^{\rho-1} d\mu^{n-1}(g_{-i}) = 0$$

The second derivative of player i's payoff is:

$$\frac{\partial^2 \pi_i \left(g_i, \mu^{n-1}\left(g_{-i}\right)\right)}{\partial g_i^2} =$$

$$= \beta \int_{supp(\mu^{n-1})} \left(\left(\frac{1-\rho}{\rho} \right) \left(g_i^\rho + \sum g_{-i}^\rho \right)^{\frac{1}{\rho}-2} \rho g_i^{\rho-1} g_i^{\rho-1} + \left(g_i^\rho + \sum g_{-i}^\rho \right)^{\frac{1-\rho}{\rho}} (\rho - 1) g_i^{\rho-2} \right) d\mu^{n-1}\left(g_{-i}\right)$$

$$= \beta \int_{supp(\mu^{n-1})} \left((1-\rho) \frac{g_i^\rho}{\left(g_i^\rho + \sum g_{-i}^\rho \right)} \left(g_i^\rho + \sum g_{-i}^\rho \right)^{\frac{1}{\rho}-1} g_i^{\rho-2} + \left(g_i^\rho + \sum g_{-i}^\rho \right)^{\frac{1}{\rho}-1} (\rho - 1) g_i^{\rho-2} \right) d\mu^{n-1}\left(g_{-i}\right)$$

$$= \beta \int_{supp(\mu^{n-1})} \left((1-\rho) \left(g_i^\rho + \sum g_{-i}^\rho \right)^{\frac{1}{\rho}-1} g_i^{\rho-2} \left(\frac{g_i^\rho}{\left(g_i^\rho + \sum g_{-i}^\rho \right)} - 1 \right) \right) d\mu^{n-1}\left(g_{-i}\right) < 0.$$

That is, $\pi_i \left(g_i, \mu^{n-1}\left(g_{-i}\right)\right)$ is globally strictly concave and g_i^* is a singleton. It follows that there is no symmetric NE in mixed strategies.

B Effects of Deviating from the Pareto Efficient Outcome

The following table reports the profits at the Pareto efficient allocation $(20, 20, 20, 20)$ and the effect of reducing g_i (own investment) on own profits and others' profits. We used the exchange rate to guarantee the same expected payment in all treatments. Obviously, the elasticity of profits with respect to own investment varies as a function of the complementary level. It is lowest at the LVCM treatment, but is around -.1 and -.05 for $\rho = 0.70, 0.65$, respectively. So reducing own investment by 10% increases own income by approximately 0.5-1%. The effect in the high complementary treatment is in the opposite direction, with elasticities of .023 and .0521 for $\rho = 0.58, .054$ respectively.

Notably, the effect on others' profits is much higher (for non-linear treatments): a reduction in g_i affects others' income much more than own income - up to almost 10 time for $\rho = 0.58$.

C Distribution of investments

Figure C.1 displays the cumulative distribution of investments by treatment (i.e., by complementarity). The plots confirm the finding of Section 4: the median investment in LVCM is zero even in the early rounds; in the case of the HC treatments, there is not much difference between the distributions under $\rho = 0.58$ and $\rho = 0.54$. Investments increase as rounds

Table B.1

Profit elasticity around the Pareto efficient allocation

Treatment Group	ρ	$\pi_i(20, 20, 20, 20)$	$\pi_i(19, 20, 20, 20)$	Elasticity of π_i wrt g_i at $(20, 20, 20, 20)$	Elasticity of π_j wrt g_i at $(20, 20, 20, 20)$
LVCM	1	\$32.00	\$32.60	-0.3750	0.25
LC	0.70	\$28.54	\$28.69	-0.1003	0.25
	0.65	\$33.13	\$33.22	-0.0502	0.2517
HC	0.58	\$34.97	\$34.93	0.0232	0.2520
	0.54	\$33.32	\$33.23	0.0521	0.2522

Note: Each cell reports profits (in Canadian dollars, after exchange rate conversion). The fifth column reports the elasticity of own profit, π_i, with respect to own investment, g_i, around the Pareto efficient allocation. For LVCM and LC a decrease in investment results in increase in profits, while in the HC treatment investment and profits are moving in the same direction. The rightmost column is the elasticity of others' profits, π_j, with respect to own investment.

progress.

By contrast, when ρ is set to 0.65 or to 0.70, the mass distribution is more heavily concentrated in the interior of the strategy space. Subjects choose to invest nontrivial amounts even after 10 rounds. For example, in rounds 11 to 20, more than half of all investments are larger than 5 tokens. Investments are range-bound and show little tendency towards convergence.

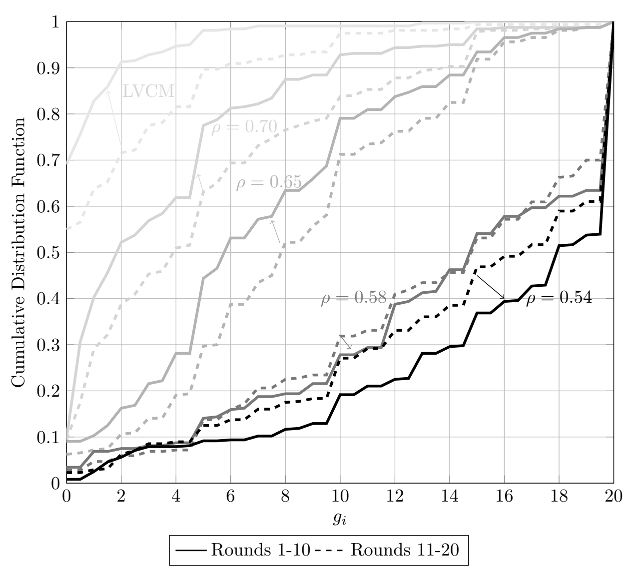

Figure C.1. Cumulative distribution functions. The dashed lines display the cumulative distribution function for the individual investments from rounds 1 to 10. The solid lines show the cumulative distribution function for the individual investments from rounds 11 to 20

.

A key feature of the production technology is that individuals not only benefit from others' investments but also enjoy incremental gains as coordination improves. The cost of less-than-perfect coordination depends on the degree of complementarity; in the linear case there is no additional loss due to lack of coordination. As complementarity increases, the impact of dispersion grows and it becomes more costly to forego coordination; on the other hand, when complementarity is high, a potential obstacle to coordination is the multiplicity of equilibria.

D Dynamic Investment Model: Estimation

The econometric model we use in Section 4 is:

$$g_{it} = \sum_{c \in \{LVCM, LC, HC\}} \beta_c D_{i,c} + \sum_{\rho \in \{1, .7, .65, .58, .54\}} \gamma_\rho X_t D_{i,\rho} + \varepsilon_{it}. \tag{D.1}$$

where $g_{i,t}$ is the investment of subject i in round t that is a function of the complementarity level (dummy variables $D_{i,c}$ where $c \in \{LVCM, LC, HC\}$) and learning is captured by the interaction of time ($X_t = {}^1\!/_t$) and the specific degree of complementarity, ρ. This model assumes that, on average and in the long-run, treatments with similar (selfish) Nash equilibria converge to the same investment level. However, the speed of learning depends on the exact complementarity degree, ρ. Given that our experiments are not immune to the presence of session-effects, we cluster standard errors at the session and individual levels, following Cameron et al. (2011) procedure. Finally, we calculate fitted values of the investments over time and their respective confidence intervals by

$$\begin{aligned}
\hat{g}_t =& \hat{\beta}_{LVCM} + X_t \times \hat{\gamma}_{\rho_1}, \text{ for LVCM} \\
\hat{g}_t =& \hat{\beta}_{LC} + X_t \left[(w_2 \times \hat{\gamma}_{\rho.7}) + (w_3 \times \hat{\gamma}_{\rho.65}) \right], \text{ for LC} \\
\hat{g}_t =& \hat{\beta}_{HC} + X_t \left[(w_4 \times \hat{\gamma}_{\rho.58}) + (w_5 \times \hat{\gamma}_{\rho.54}) \right], \text{ for HC}
\end{aligned}$$

where w_j are weights based on the number of sessions per treatment. The outcome of the estimated equation is shown in Table D.1.

Table D.1

Estimation of Equation D.1

D_{LVCM}	0.589
	(0.42)
D_{LC}	5.562***
	(1.67)
D_{HC}	15.197***
	(1.25)
$D_{LVCM} \times X_t$	4.325***
	(1.38)
$D_{.7} \times X_t$	0.281
	(3.54)
$D_{.65} \times X_t$	6.807**
	(2.78)
$D_{.58} \times X_t$	-4.190*
	(2.26)
$D_{.54} \times X_t$	-2.408
	(2.57)
Observations	3,520
R^2	0.8107

Note: Clustered standard errors are in parentheses. $^*p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$

E Mechanical Use of the Calculator

In what follows we report additional information about the way subjects use the calculator. In Table E.1 we show the summary statistics of the mechanical use of the calculator for different types and treatments. We examine the following variables: (a) *CalcRound*, number of rounds the calculator was used by a subject, (b) *Hyp*, number of own hypothetical investments entered in the calculator, (c) *Conj*, number of conjectures about other players' investments that were entered into the calculator, and (d) *Hyp per Conj*, number of own hypothetical investments entered, given a conjecture about other players' investments.

Number of rounds. Table E.1 confirms that the LVCM is arguably the easiest environment for Type 1 subjects: they end up using the calculator very little (in only 4.6 rounds).[22] In contrast, Type 2 agents use the calculator in the LVCM as much as in other

[22] Three Type 1 participants did not even activate the calculator after the practice round.

LC treatments. This suggests that Type 1 may use the calculator to identify the BR and then mechanically play it to maximize pecuniary rewards.

The degree of complementarity noticeably affects calculator usage: subjects in LC treatments use the calculator in twice as many rounds as subjects in HC sessions. This supports the view that subjects find it easier to calculate BR strategies in HC treatments.[23] For example, when $\rho = 0.54$, the BR is to invest the whole endowment in the group account if other group members invest at least half of their endowment; this means that, after a few rounds, agents may effectively adopt something close to a high-investment strategy, which requires no further refinement through the use of the calculator. In LC treatments, instead, choosing a strategy that maximizes payoff requires more fine tuning. For example, when $\rho = 0.70$, a subject would optimally choose to invest one quarter of the average investment made by others to maximize her payoff, assuming all other players invest the same amount. Hence, it may be harder to identify a BR strategy in LC treatments.

Conjectures and hypothetical choices. Looking at conjectures, and at the number of own hypothetical choices per conjecture, there is no significant difference across types in LVCM and LC. Subjects in LC and HC treatments enter more hypothetical choices than in LVCM. A Type 1 subject enters on average slightly more hypothetical investments per conjecture than does a Type 2 subject in the LC and the HC sessions. One may expect this behavior from an individual who is very concerned about maximizing her money earnings.

[23]Six subjects in the HC treatment did not use the calculator after the practice period.

Table E.1

Differences in Mechanical Use of the Calculator, by Subject Type Within Complementarity Level

	LVCM			LC			HC		
	Type 1	Type 2	p-value from a t-test	Type 1	Type 2	p-value from a t-test	Type 1	Type 2	p-value from a t-test
CalcRound	4.6 (1.1)	6.5 (1.5)	0.3	11.0 (0.9)	10.2 (0.9)	0.5	6.1 (0.6)	6.3 (1.3)	0.7
Hyp	17.2 (2.4)	22.1 (3.4)	0.2	30.1 (2.1)	31.2 (2.9)	0.8	29.4 (2.4)	14.9 (1.4)	0
Conj	14.1 (1.0)	14.0 (1.2)	1.0	15.0 (0.6)	16.4 (0.7)	0.1	10.9 (0.4)	9.1 (0.7)	0
Hyp Per Conj	3.7 (0.4)	4.3 (0.5)	0.3	7.2 (0.5)	6.6 (0.6)	0.24	8.2 (0.7)	5.1 (0.6)	0
Observations	17	15		39	25		54	24	

Note: Each cell reports the average value for the respective category (standard errors are reported in parentheses). The t-tests of the means are reported in the third column of each treatment. *CalcRound*, number of rounds in which subjects used the calculator; *Hyp*, number of hypothetical own investments; *Conj*, number of conjectures about others; *Hyp per Conj,* number of own hypothetical investments entered, given a conjecture about other players' investments. We include the practice rounds.

E.1 Persistence of Conjectures

In Table E.2 we show the total number of conjectures per round. Note that there is a significant decrease in the percentage of innovations over time, especially in HC treatments. This suggests that some subjects form conjectures early in the experiment that do not change much.

Table E.2
Persistence of Conjectures

	LVCM		LC		HC	
Round	No. of New Conjectures	Overall Conjectures	No. of New Conjectures	Overall Conjectures	No. of new Conjectures	Overall Conjectures
Practice	400	400	782	782	719	719
1	5	38	33	131	20	115
2	4	23	26	100	22	76
3	4	28	22	105	15	62
4	5	18	19	95	11	71
5	5	26	20	86	5	55
6	6	25	16	91	9	41
7	0	8	15	70	2	39
8	2	13	13	72	9	56
9	3	12	10	80	4	35
10	3	6	6	58	3	29
11	5	12	7	65	3	41
12	2	8	5	60	1	21
13	1	5	3	45	2	23
14	0	9	2	42	0	21
15	1	9	5	44	0	19
16	1	5	3	40	3	18
17	0	3	6	49	1	9
18	1	4	3	45	0	17
19	1	4	0	33	0	20
20	0	4	1	31	3	27

F History-Dependent Conjectures

This Appendix provides evidence of history dependence of subjects' beliefs about others. We assess the length of the subjects' memory span by regressing the conjectures about others' investments on the actual investments by group partners in the previous five rounds. Table F.1 reports the results, showing that subjects' conjectures respond significantly to investments made by other members in the previous two rounds.

Table F.1

Response of Subjects' Conjectures to Others' Investments

	$\left(\frac{1}{n-1}\sum g_{-i}^{\rho}\right)^{1/\rho}$	$\frac{1}{n-1}\sum g_{-i}$
$F\left(g_{-i,t-1}\right)$	0.541***	0.557***
	(0.05)	(0.06)
$F\left(g_{-i,t-2}\right)$	0.209***	0.211***
	(0.07)	(0.07)
$F\left(g_{-i,t-3}\right)$	0.035	0.023
	(0.04)	(0.04)
$F\left(g_{-i,t-4}\right)$	-0.008	-0.009
	(0.05)	(0.05)
$F\left(g_{-i,t-5}\right)$	0.072*	0.067
	(0.04)	(0.04)
Constant	1.414***	1.358***
	(0.45)	(0.44)
Observations	1,603	1,605

Note: We estimate the following least-squares specification: $F\left(\hat{g}_{-i,t}\right) = C + \sum_{L=1}^{5} A_L F\left(g_{-i,t-L}\right) + u_{i,t}$, where $\hat{g}_{-i,t}$ is a vector of player i's conjectures about other group members' investments in period t, $g_{-i,t-L}$ contains the vector of investments made by other members in round $t-L$, C is a common constant, and $u_{i,t}$ is an idiosyncratic error. We let the function $F(\cdot)$ be either the arithmetic or the generalized mean of degree ρ. The standard errors (reported in parentheses) are clustered by individuals and obtained by bootstrap estimations with 1,000 replications. *$p < 0.1$, **$p < 0.05$, ***$p < 0.01$. As a robustness check, we also estimate this specification including dummy variables to control for different treatments. Results are very similar.

G Best-Response Range and Investments

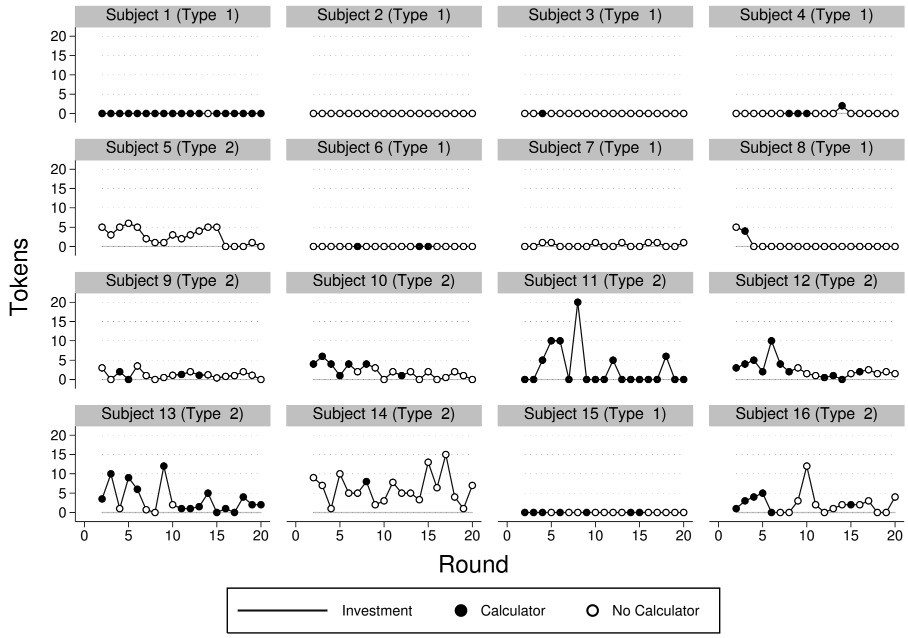

Figure G.1. Session 1 (LVCM)

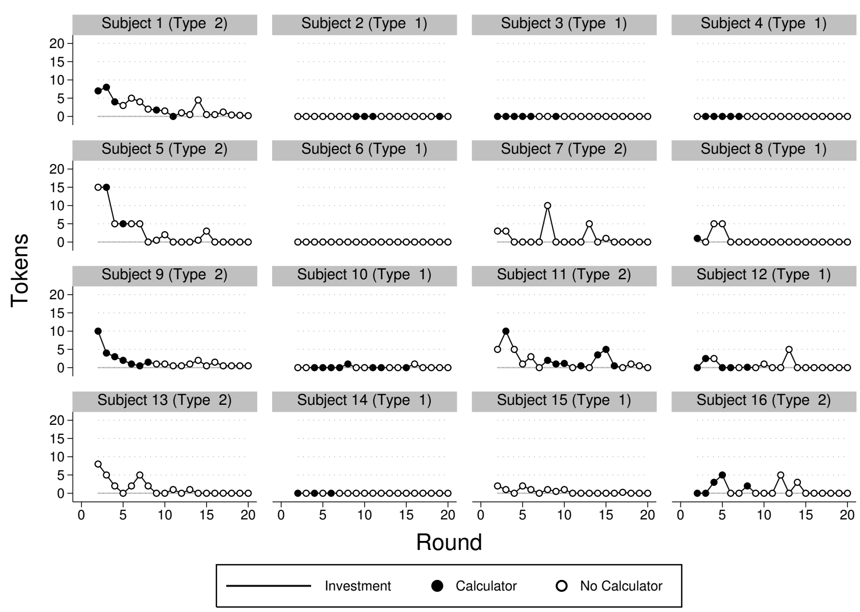

Figure G.2. Session 2 (LVCM)

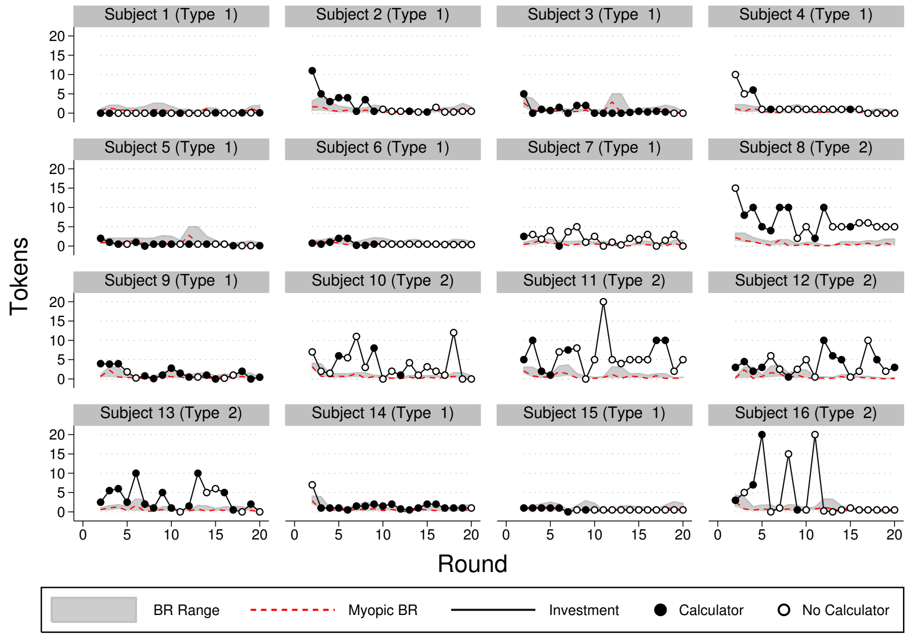

Figure G.3. Session 3 ($\rho = 0.70$)

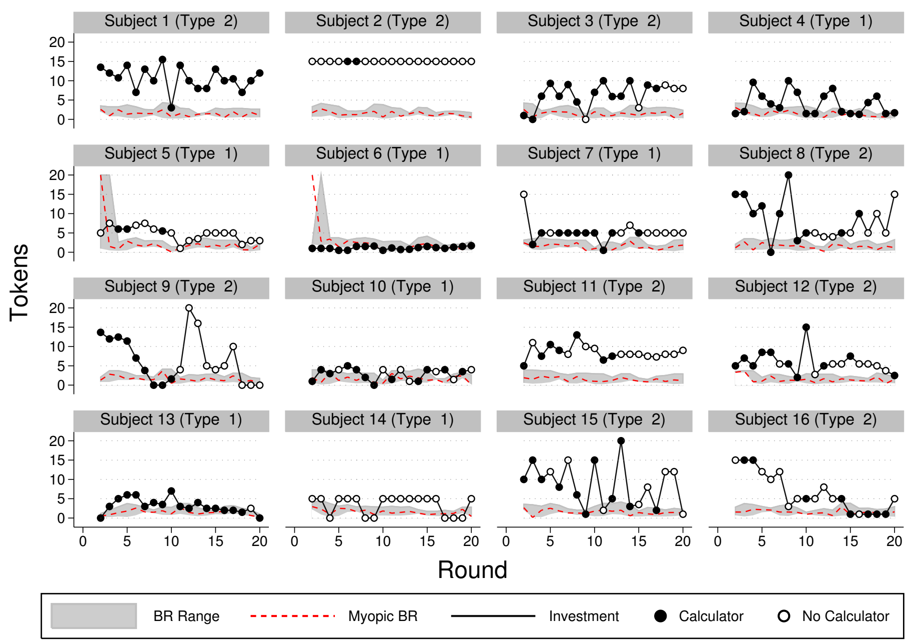

Figure G.4. Session 4 ($\rho = 0.70$)

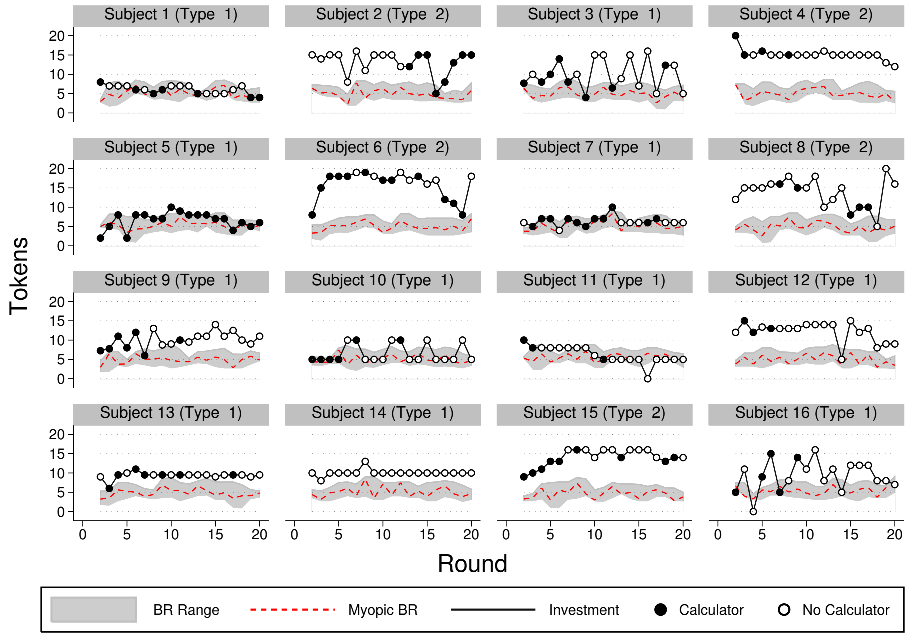

Figure G.5. Session 5 ($\rho = 0.65$)

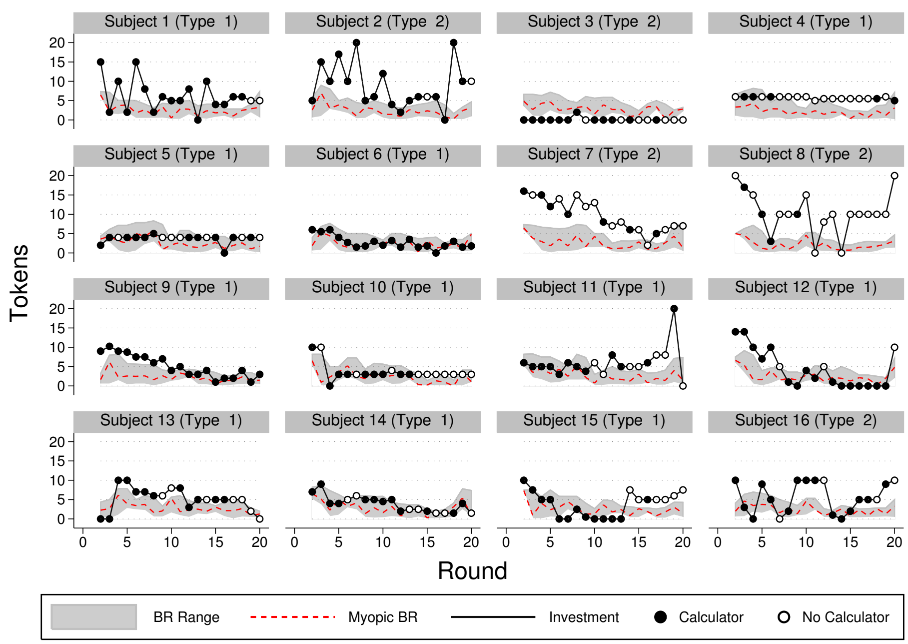

Figure G.6. Session 6 ($\rho = 0.65$)

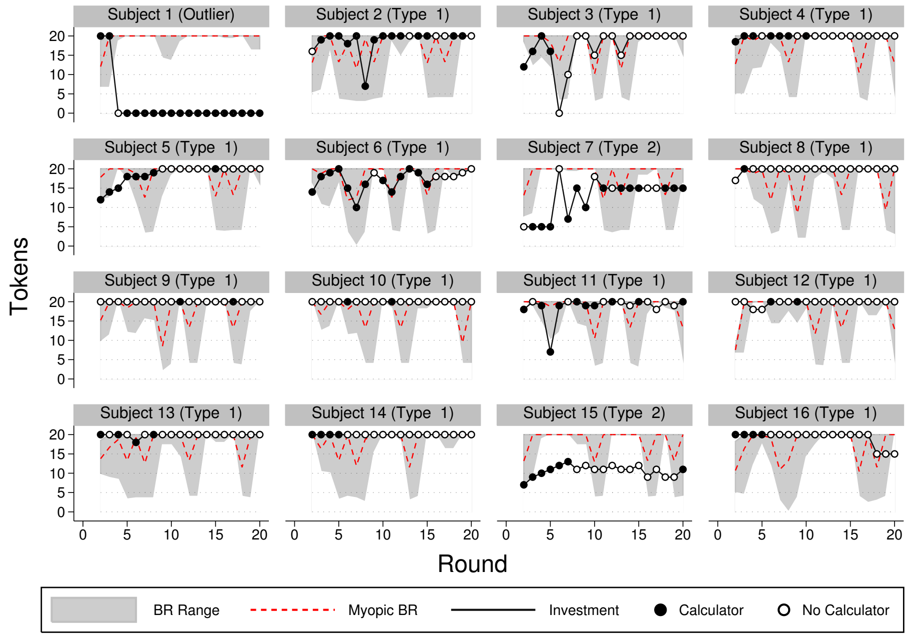

Figure G.7. Session 7 ($\rho = 0.58$)

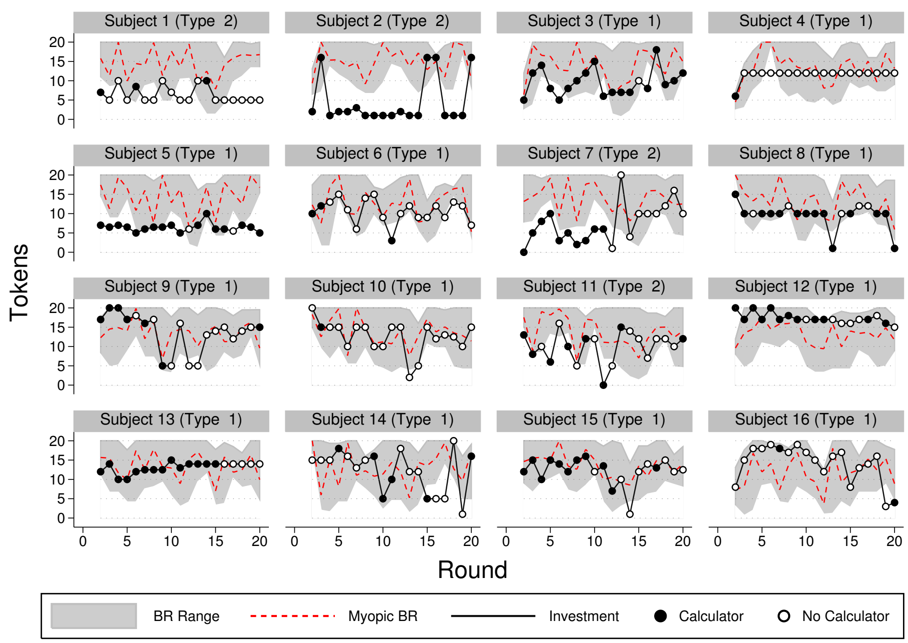

Figure G.8. Session 8 ($\rho = 0.58$)

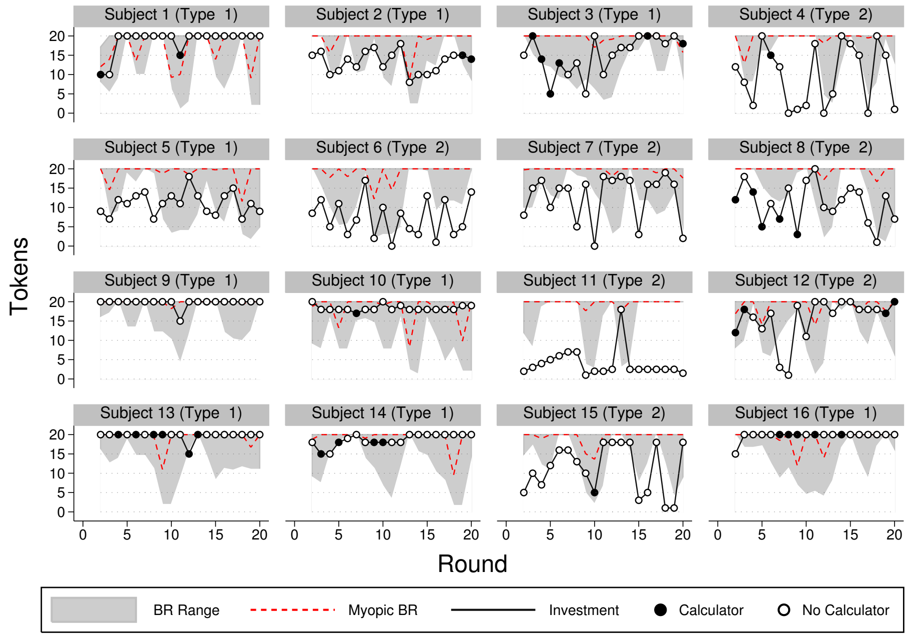

Figure G.9. Session 9 ($\rho = 0.54$)

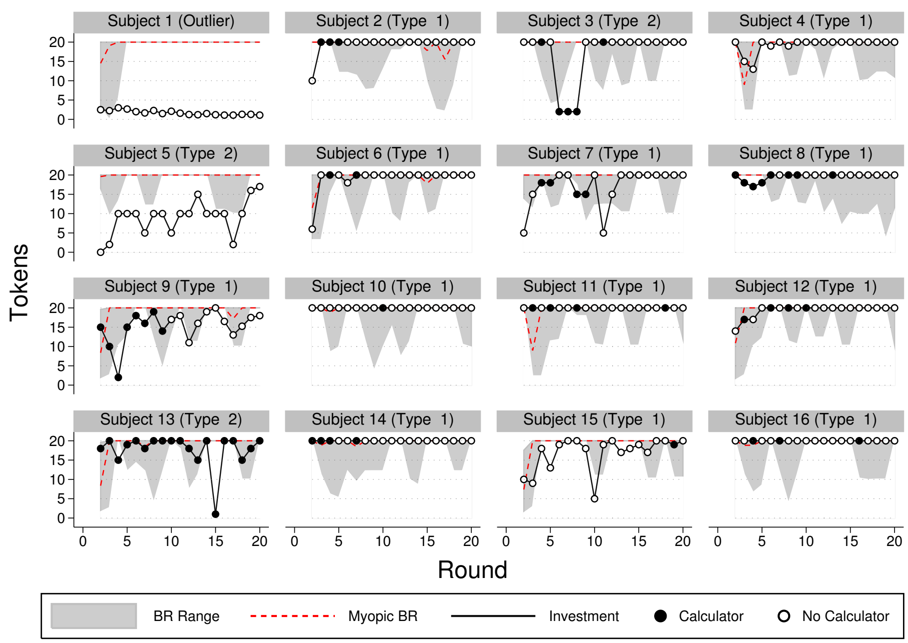

Figure G.10. Session 10 ($\rho = 0.54$)

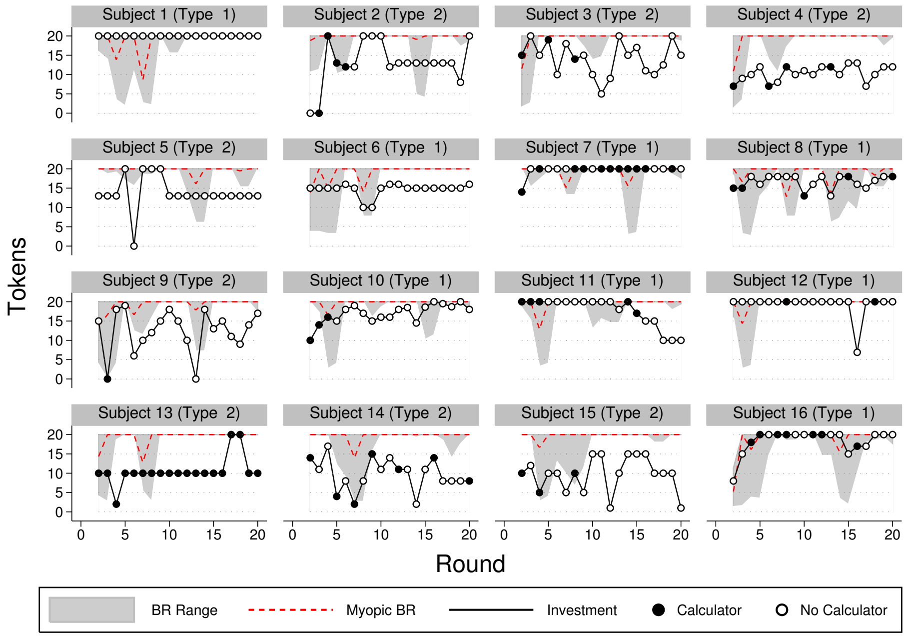

Figure G.11. Session 11 ($\rho = 0.54$)

H Calculator Usage and Investments

H.1 Evolution of conjectures: training, early, and later rounds

To examine the role of training we compare the initial conjectures concerning others' investments across different treatments. Table H.1 shows the average of the generalized mean of the conjectures in each treatment. As discussed in the Introduction and Section 3.2, and analyzed extensively in Section 5, we did not elicit beliefs. Instead, we collected data on the inputs subjects entered in the payoff calculator. We use conjectures about group members' investments to describe beliefs about others. The first column (Practice) of Table H.1 shows that conjectures made during the practice period, before the experiment started, do not differ on average across treatments, as subjects are still learning about the payoff space. However, starting from round 1 (column 2) growing differences emerge across treatments. These difference reflect the evolution of investments that appears in Figure 4.1.

Table H.1
Average Conjecture About Others' Investments

Treatment	Practice (1)	Round 1 (2)	Round 2 (3)	Round 5 (4)	Round $\geq$ 10 (5)
LVCM	9.16	6.61	5.24	3.66	2.98
	(0.33)	(0.85)	(0.77)	(1.01)	(0.85)
LC	9.17	9.33	8.26	5.97	5.75
	(0.37)	(0.87)	(1.19)	(0.81)	(0.90)
HC	9.03	10.76	10.53	13.10	12.60
	(0.36)	(0.71)	(1.56)	(1.69)	(1.65)
No. of conjectures	5,213	357	249	204	961

Note: Each cell reports the average value for the generalized mean of the conjectures of others' investments (standard errors are reported in parentheses). Standard errors are clustered at the individual and session level, as in D.1.

H.2 Investments of calculator users and non-users

Table H.2 displays the distribution of types for subjects that activated the calculator at least once from rounds 16 to 20 and subjects that did not.

Table H.2

Distribution of Types by Calculator Usage

Type	LVCM		LC		HC		Total
	Calc	No Calc	Calc	No Calc	Calc	No Calc	
1	2	15	24	15	20	34	114
2	4	11	17	8	8	16	60
Total	6	26	41	23	28	50	174

Treatment Group: LVCM, LC, HC.

Note: Each cell reports the number of subjects that activated the calculator (Calc) and the number of those who did not activate the calculator (No Calc) in rounds 16-20 by treatment group and type.

Figure H.1 shows the distribution of investments (hypothetical and actual) by the degree of complementarity and calculator activation (users/non-users) during the last five rounds. Each sub-figure depicts (separately) Type 1 and Type 2 subjects, as well as pecuniary best-response to investments.

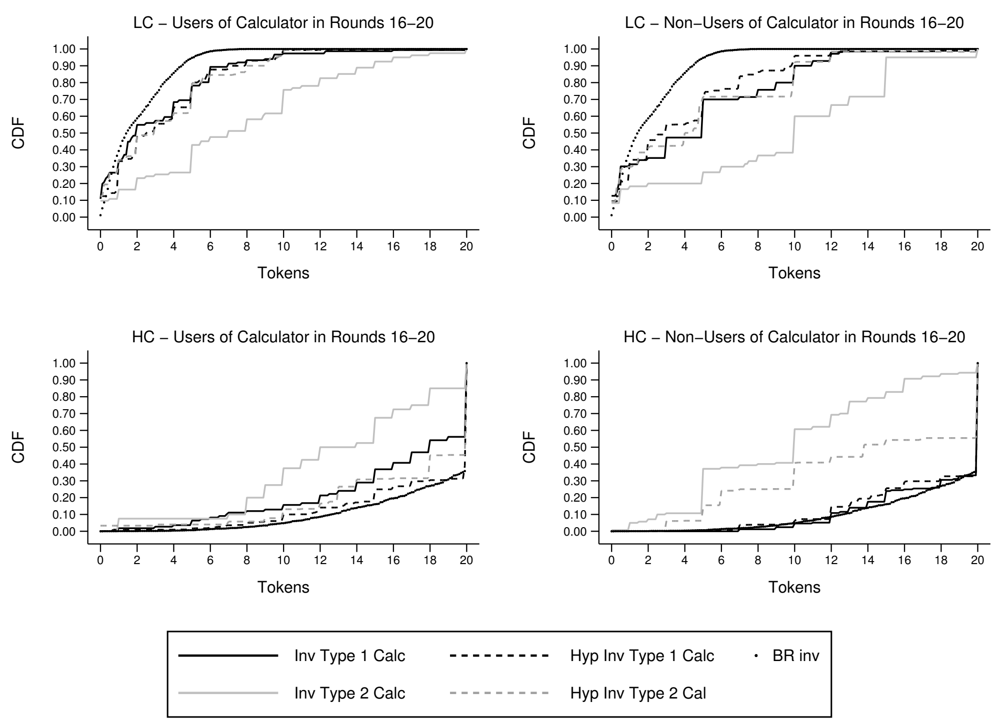

Figure H.1. CDF of Actual and Hypothetical Investments by Type and Calculator Activation (Rounds 16-20).

I *Hypothetical Investments and Loss Indices*

In this section we describe the procedures employed to recover the Cumulative Distribution Functions (CDF) of hypothetical investments and generate histograms for the *Hypothetical Loss Index* and the *Behavioral Loss Index.*

I.1 CDF of Hypothetical Investments

1. Consider all conjectures entered in the calculator by all subjects in all rounds. Each conjecture $\hat{g}_{-i} = (\hat{g}_2, \hat{g}_3, \hat{g}_4)$ is a triplet of values (one for each of the members in a subject's group). For each conjecture, we compute the generalized mean $M_\rho(\hat{g}_{-i}) = \left(\frac{\hat{g}_2^\rho + \hat{g}_3^\rho + \hat{g}_4^\rho}{3}\right)^{\frac{1}{\rho}}$.

2. We partition the set of generalized means from step 1 into separate intervals (the intervals are shown in Table I.1), depending on how the pecuniary best-response changes as a function of $M_\rho(\hat{g}_{-i})$.

3. With slight abuse of notation, we use all entries the subjects made into the "hypothetical investment" field of the calculator, from all rounds, to identify the one that maximizes the pecuniary payoff within each of the intervals (defined in step 2) containing her conjectures. As each interval corresponds to a set of conjectures that result in approximately the same pecuniary-optimal investment, the *hypothetical investment* is the value that generates the highest pecuniary return among all investments considered in that interval. We use all rounds because some subjects may identify the investment that maximizes their pecuniary payoff, given their conjectures, in early rounds.

4. When observing the hypothetical investments within each interval, it is important to recognize that some subjects enter only few conjectures while others enter many. To account for this heterogeneity in calculator usage, we weight the hypothetical investments in each interval. For example, suppose that subject x and subject y participate in the same session. Suppose also that there are only two intervals: 1 and 2. Subject x has a single conjecture (say, in interval 1), while subject y enters two conjectures (one in each interval). Then, the hypothetical investment of subject x in interval 1

is assigned twice the weight as that of subject y. Therefore, the weights of the hypothetical investments of subjects x and y in interval 1 are $2/3$ and $1/3$, respectively. This avoids a scenario in which participants who enter many conjectures contribute a disproportionately large amount of information to the distribution of hypothetical investments.

5. Given weights from step 4, we recover a cumulative distribution function of hypothetical investments for each type (t), session (s) and interval.

6. To assign higher weights to hypothetical investments that are relevant in the last five rounds, we re-weight them using the actual investments in rounds 16 to 20, as described in steps 7-9 below.

7. From the empirical distribution of investments, we draw 1,000 triplets at the session level (we draw only from rounds 16 to 20, i.e. the last five), denoted by $g_{-i,s} = (g_2, g_3, g_4)$. For each triplet $g_{-i,s}$ we calculate the generalized mean, $M_\rho(g_{-i,s}) = \left(\frac{g_2^\rho + g_3^\rho + g_4^\rho}{3}\right)^{\frac{1}{\rho}}$.

8. For each session, we partition the set of generalized means (obtained in step 7) into separate intervals (the intervals are shown in Table I.1). Then, we assign a frequency value to each interval based on the share of the generalized means contained within it. This accounts for the fact that some intervals are more frequent than others.

9. We take the distributions of hypothetical investments computed in step 5 (one for each type, session and interval). Fixing session and type, we calculate the distribution of hypothetical investments over the whole range of generalized means as the mixture of interval-specific distributions of hypothetical investments, weighted by the relative frequencies of observations within each interval (obtained in Step 8). This results in a CDF of hypothetical investments (one such distribution for each session and type), which we denote by $\hat{g}_{t,s}$.

10. To calculate the CDF at the treatment level (like the ones shown in Figure 5.3), one must combine the CDF of the sessions within each treatment. This is done by

calculating their simple average. Specifically, for each probability value in the CDFs, we take the average over the hypothetical investments associated with such value. For example, suppose that there are two sessions in a given treatment. In the first one, 50 percent of the hypothetical investments are lower than or equal to 10 tokens. While in the second one, 50 percent of the hypothetical investments are lower than or equal to 18 tokens. In the combined CDF, 50 percent of the hypothetical investments would be lower than or equal to 14 tokens.

I.2 *Computation of "Hypothetical Loss Index"* and *"Behavioral Loss Index"*

1. For each subject type t and experiment session s, we randomly draw 1,000 values from the empirical distribution of actual investments (we draw from rounds 16 to 20, i.e. the last five). We denote an element of this set of draws as $g_{m,t,s}$, where $m \in \{1, \ldots, 1000\}$ is a draw, t denotes type and s is the session.

2. Using the pooled distribution of investments (pooling together Type 1 and Type 2), we draw 1,000 triplets (conditioning at the session level; for rounds 16 to 20). We call the elements of this set $g_{-i,s}$, where $i \in \{1, \ldots, 1000\}$ is a triplet draw, and s is the session.

3. Denote the pecuniary best-response to each $g_{-i,s}$ by $g^*(g_{-i,s})$.

4. We randomly draw 1,000 values from the CDF of hypothetical investments of each session s and type t (these distributions are generated using the procedures described in subsection I.1). We denote each element of this set as $\hat{g}_{m,t,s}$, where $m \in \{1, \ldots, 1000\}$ is a hypothetical investment draw.

5. To each element $g_{m,t,s}$ from step 1 (i.e. for each draw m of type t and session s) we randomly assign a hypothetical investment draw $\hat{g}_{m,t,s}$ from step 4. Then, for each such pair $(g_{m,t,s}, \hat{g}_{m,t,s})$ we randomly assign an element $g_{-i,s}$ from step 2 (i.e. a triplet $-i$ from session s). This is done separately for each session.

6. Using the values $(g_{m,t,s}, \hat{g}_{m,t,s}, g_{-i,s})$ from step 5, we can then compute pecuniary payoff functions $\pi\left(\hat{g}_{m,t,s}, g_{-i,s}\right)$, $\pi\left(g^*(g_{-i,s}), g_{-i,s}\right)$ and $\pi\left(g_{m,t,s}, g_{-i,s}\right)$.

7. Steps 5 and 6 allow us to decompose the monetary loss (due to the discrepancy between actual investment and best-response) into two complementary elements: (i) the loss due to deviation of hypothetical investment from best-response; and (ii) the loss due to deviation of actual investment from hypothetical investment.

8. We compute the *Hypothetical Loss Index* and the *Behavioral Loss Index* as follows:

   (a) $Hypothetical\ Loss\ Index = \frac{\pi(\hat{g}_{m,t,s},g_{-i,s})-\pi(g^*(g_{-i,s}),g_{-i,s})}{\pi(g^*(g_{-i,s}),g_{-i,s})} \times 100$

   (b) $Behavioral\ Loss\ Index = \frac{\pi(g_{m,t,s},g_{-i,s})-\pi(\hat{g}_{m,t,s},g_{-i,s})}{\pi(g^*(g_{-i,s}),g_{-i,s})} \times 100$

9. This results in 1,000 such measures for each session s. We use these measures to characterize the distribution of pecuniary losses in the population.

Table I.1
Intervals for the Generalized Mean of Investments

Intervals	[0,2.5]	[2.5,5)	[5,7.5)	[7.5,10)	[10,12.5)	[12.5,15)	[15,17.5)	[17.5,20]
$\rho = 1$	1	1	1	1	2	2	2	2
$\rho = 0.70$	1	2	3	4	5	6	7	8
$\rho = 0.65$	1	2	3	4	5	6	7	8
$\rho = 0.58$	1	2	3	4	5	6	7	7
$\rho = 0.54$	1	2	3	4	5	5	5	5

Note: Elements of partition for each ρ are identified by the same number. For example, for $\rho = 0.54$ there are 5 elements in the partition since for $M_\rho\left(\hat{g}_{-i}\right) \geq 10$ the pecuniary best response is 20.

I.3 Tests to Compare Cumulative Distribution Functions

Because the CDFs are mixtures of different values of ρ, one cannot use standard non-parametric tests to compare them. Instead, we draw 1,000 random samples from the corresponding CDFs. We then implement a rank-sum test under the null hypothesis that the distributions are identical between each pair of samples. The sample size is based on the number of observations in each session. For example, for the distribution of investments in session s, the sample size is 80 (16 subjects $\times$ 5 rounds).

I.3.1 Actual Investments vs Conjectures by Type

The null hypothesis is that conjectures are coherent (for example, conjectures of Type 1 in LC are distributed similarly to investments in LC). In LC, we cannot reject the null (at a 95% confidence level) for Type 1 in 96.2 percent of the tests. For Type 2 we fail to reject in 75.9 percent of the tests. In HC, we fail to reject the coherence of conjectures in 91.2 percent of the tests for Type 1 (90.6 percent for Type 2).

I.3.2 Actual Investments by Type

When we test whether the distributions of investments of different types are equal (separately done in LC and HC treatments), we always reject the null hypothesis (at a 95% confidence level).

I.3.3 Hypothetical Investments by Type

When we consider the null hypothesis that the distributions of hypothetical investments of different types (Type 1 vs Type 2) are identical, we cannot reject the null in LC treatments (at a 95% confidence level) in 93.8 percent of the tests. For HC, we fail to reject in 40.3 percent of the tests.

I.3.4 Hypothetical Investments vs Actual Investments by Type

The null hypothesis is that the distributions of hypothetical and actual investments are identical for each type. For Type 1, we cannot reject the null (at a 95% confidence level) in 86.8 percent of the tests in LC, and for 68 percent of the tests in HC. For Type 2, we always reject the null (at a 95% confidence level) in both LC and HC.

J Computer Interface

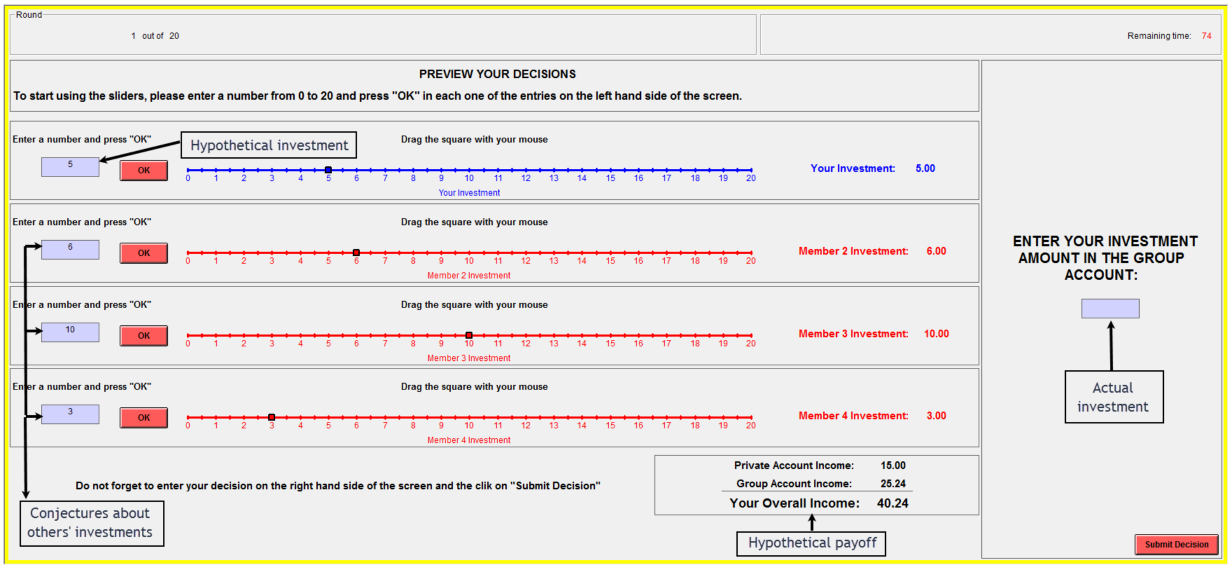

Figure J.1. Main computer interface

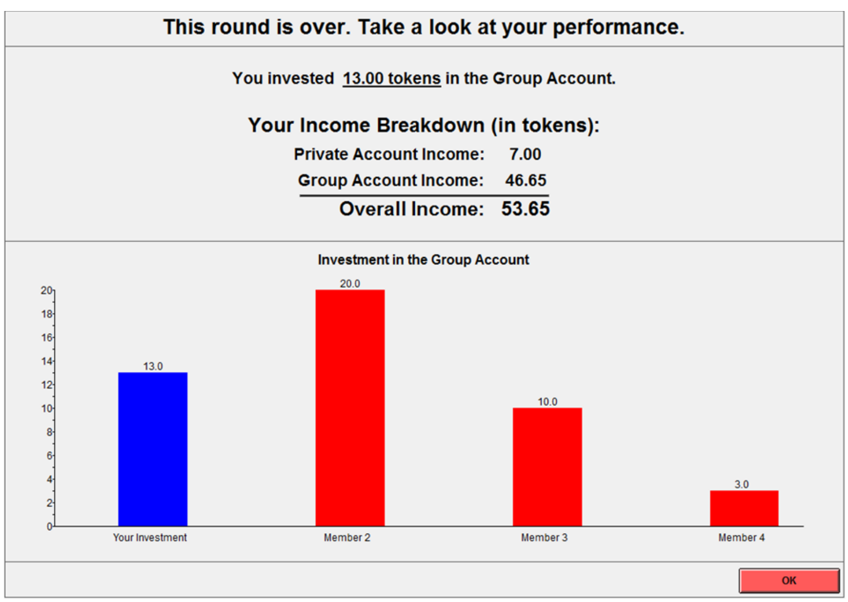

Figure J.2. Feedback

K Control Questions

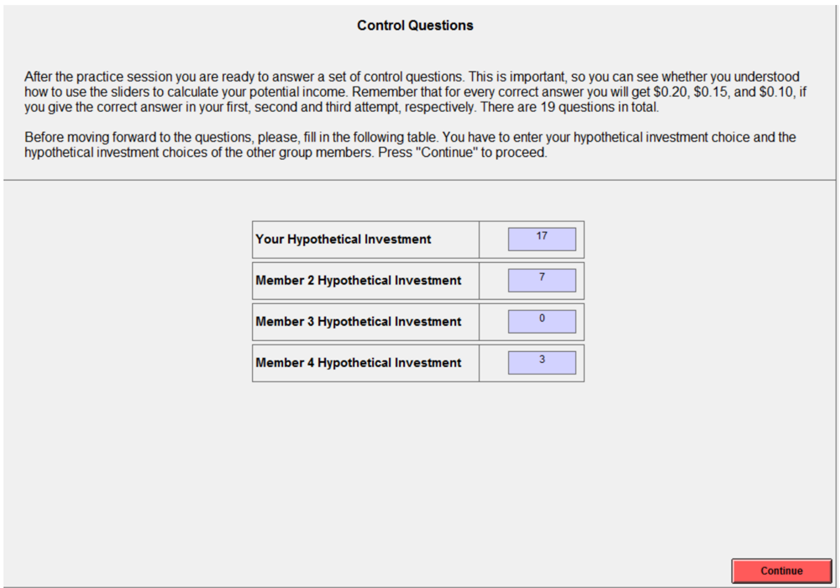

Figure K.1. Control question 1/7

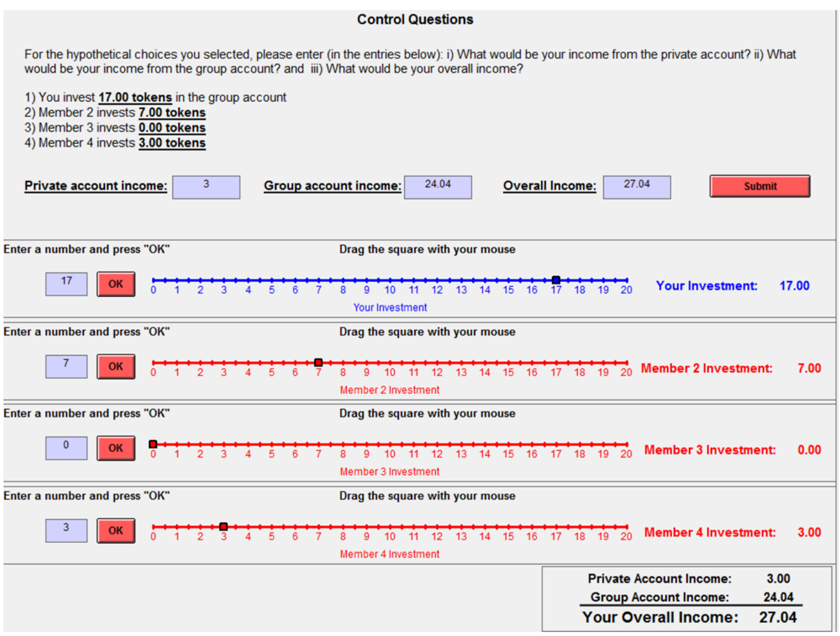

Figure K.2. Control question 2/7

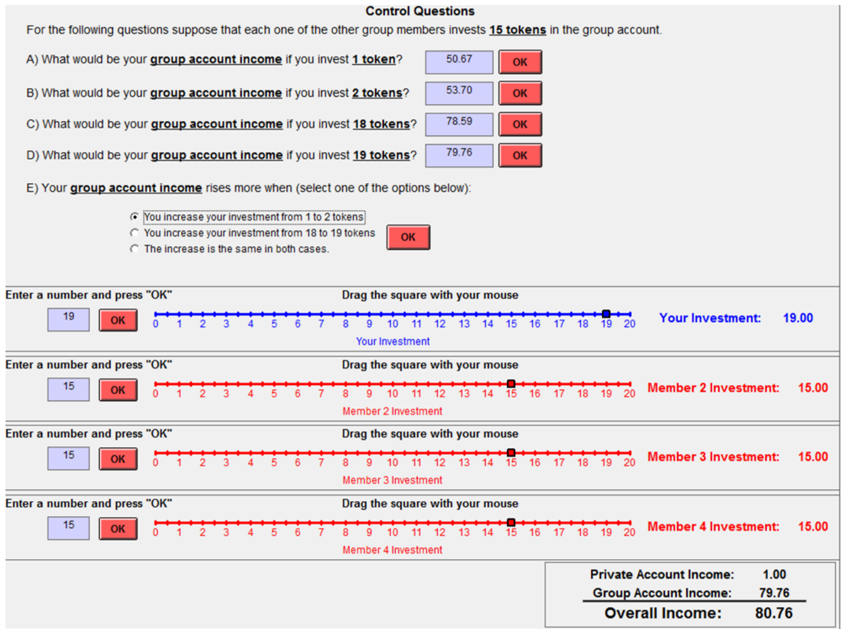

Figure K.3. Control question 3/7

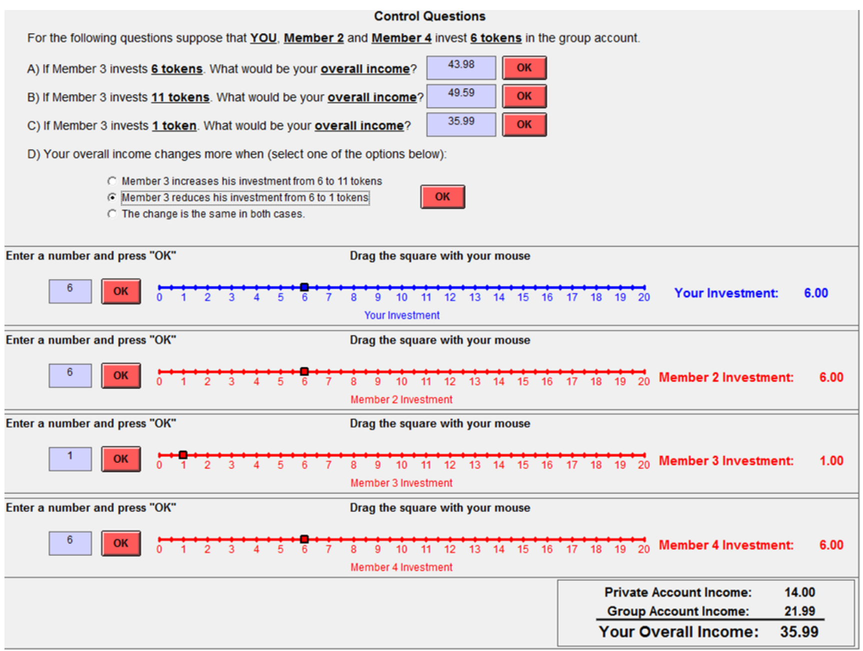

Figure K.4. Control question 4/7

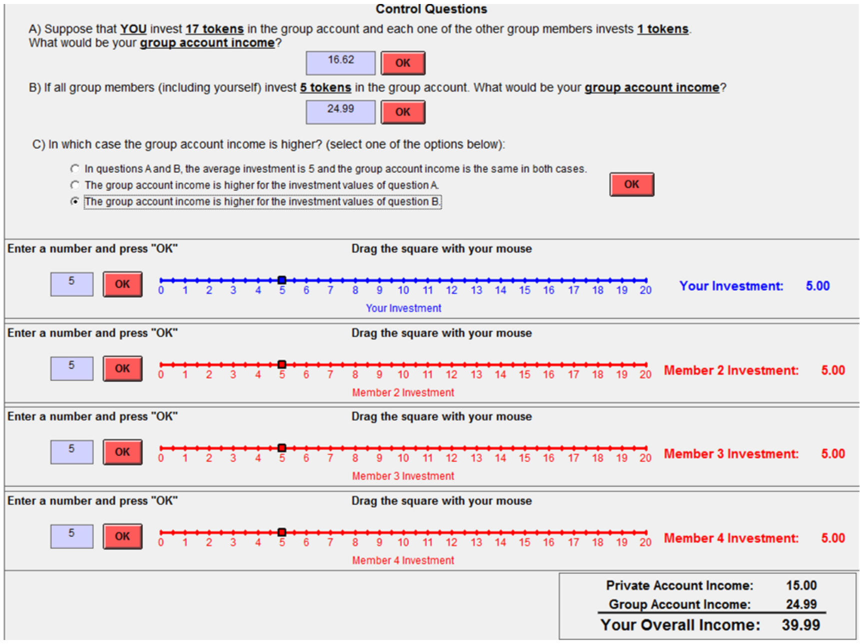

Figure K.5. Control question 5/7

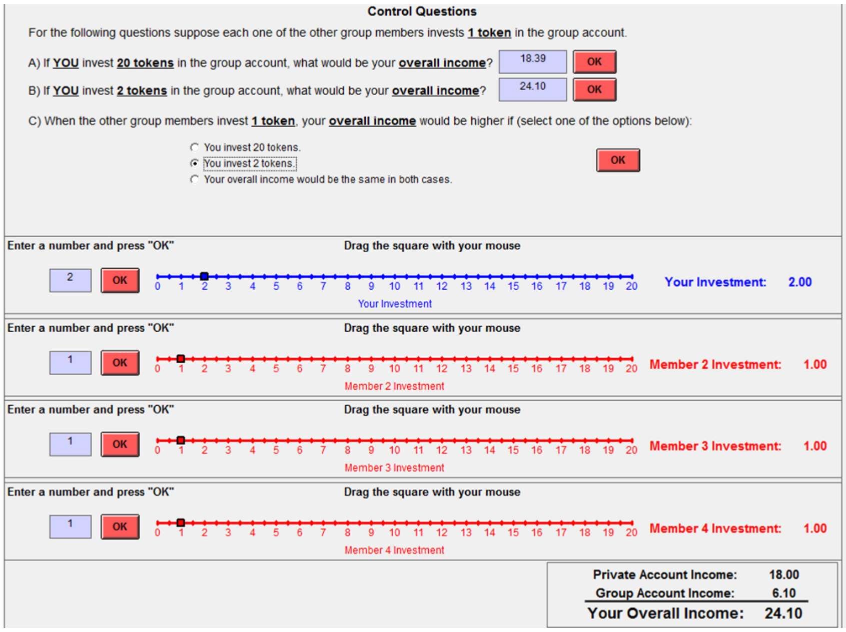

Figure K.6. Control question 6/7

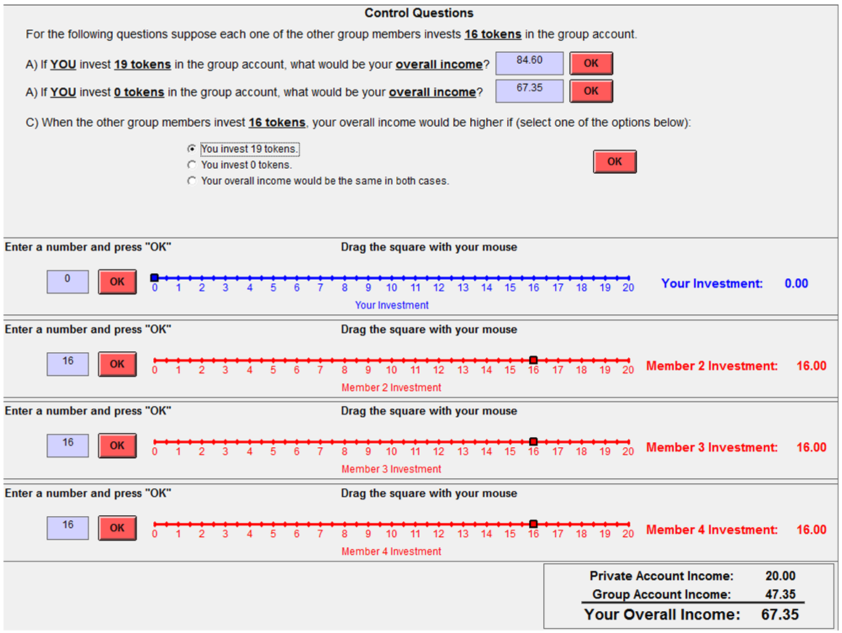

Figure K.7. Control question 7/7

L Instructions

The instructions distributed to subjects in all the treatments are reproduced on the following pages. All subjects received the same set of instructions except that those in the LVCM treatment received the following explanation about how the income from the group account was calculated:

> The total group income depends on the investments of all group members, and it is shared equally among all group members. This means that each group member receives one quarter (1/4) of the total group income.
> Some important points to keep in mind:
> a. The more you and others invest in the group account, the higher the total group income.
> b. The group income is obtained by multiplying the sum of the investments of all group members by 1.6 (remember that the resulting group income is shared equally among group members).

The exchange rate was adjusted so that the monetary payoff in the Pareto efficient outcome was the same across all treatments.

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Instructions

You are taking part in an economic experiment in which you will be able to earn money. Your earnings depend on your decisions and on the decisions of the other participants with whom you will interact. It is therefore important to read these instructions with attention. You are not allowed to communicate with the other participants during the experiment.

All the transactions during the experiment and your entire earnings will be calculated in terms of tokens. At the end of the experiment, the total amount of tokens you have earned during this session will be converted to CAD and paid to you in cash according to the following rules:

1. The game will be played for 20 rounds. At the end of the experiment, the computer will randomly select one of your decision rounds for payment. That is, there is an equal chance that any decision you make during the experiment will be the decision that counts for payment.

2. The amount of tokens you get in the randomly selected round will be converted into CAD at the rate: 2 tokens = $1.

3. You will get $0.20 for every control question you answer correctly in the first attempt; $0.15 for every question you answer correctly in the second attempt; and $0.10 for every question you answer correctly in the third attempt.

4. In addition, you will get a show-up fee of $5.

Introduction

This experiment is divided into different rounds. There will be 20 rounds in total. In each round you will obtain some income in tokens. The more tokens you get, the more money you will be paid at the end of the experiment.

During all 20 rounds the participants are divided into groups of four. Therefore, you will be in a group with 3 other participants. **The composition of the groups will change every round.** You will meet each of the participants only four times, in randomly chosen rounds. However, each time you are matched with a participant that you encountered before, the other group members will be different. This means that the group composition will never be identical in any two rounds. Moreover, **you will never be informed of the identity of the other group members.**

Description of the rounds

At the beginning of the rounds each participant in your group receives 20 tokens. We will refer to these tokens as the initial endowment. Your only decision will be on how to use your initial endowment. You will have to choose how many tokens you want to invest in a group account and how many of them

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you'll want keep for yourself in a private account. You can invest any amount of your initial endowment in the group account.

The decision on how many tokens to invest is up to you. Each other group member will also make such a decision. All decisions are made simultaneously. That is, nobody will be informed about the decision of the other group members before everyone made his or her decision.

End of the rounds

At the end of each round (after all choices are submitted), you will see: (i) your investment choice, (ii) the investment choices of the other members in your group, and (iii) your income. Then, next round starts automatically and you will receive a new endowment of 20 tokens.

Income calculation

Each round, your total earnings will be calculated by adding up the income from your private account and the income from the group account:

1. Income from your private account. You will earn 1 token for every token you keep in you private account. If for example, you keep 10 tokens in your private account your income will be 10 tokens.

2. Income from the group account. The total group income depends on the investments of all group members, and it is shared **equally** among all of them. That is, each group member receives one quarter (1/4) of the total group income.

Some important points to keep in mind:

a. The more you and others invest, the higher the **total** group income.
b. Taking as given the investments of all other group members, consider two levels for your investment in the group account (say, low investment and high investment). Next, increase both the low investment and the high investment by 1 token. The total group income will increase in both cases. However, the increase is smaller in the case of the higher investment level.
c. When you increase your investment in the group account, the total income will not increase at a constant rate. The rate depends on the value of all participants' investments in the group account.
d. For the same average investment in the group account, the total group income would be higher if there is not much difference between the investments chosen by each one of the group members.
e. If all other members in your group invest zero, the total group income will be determined by multiplying your investment in the group account by **1.6**; the resulting amount is the group income and it will be shared equally among all group members.

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Using the calculator to compute your income

To calculate your potential income you will have access to a calculator (look at the picture below).

To activate the calculator, you will be asked to fill in a hypothetical value for your own investment and for the other group members' investment; then, you will be able to visualize your income for such hypothetical investment choices. You can consider as many hypothetical investment combinations as you want.

Before the experiment starts you'll understand how to use the calculator; you will be able to practice with it; and finally, you will have to answer some control questions. For every correct answer you will get $0.20, $0.15, $0.10 if you give the correct answer in the first, second and third attempt, respectively.

<u>Remember that your actual investment decision has to be entered on the right hand side of the screen. Every round you will have 95 seconds to do that.</u>

Screen-shot of the experiment interface